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Evaluating the adoption and impacts of agricultural technologies

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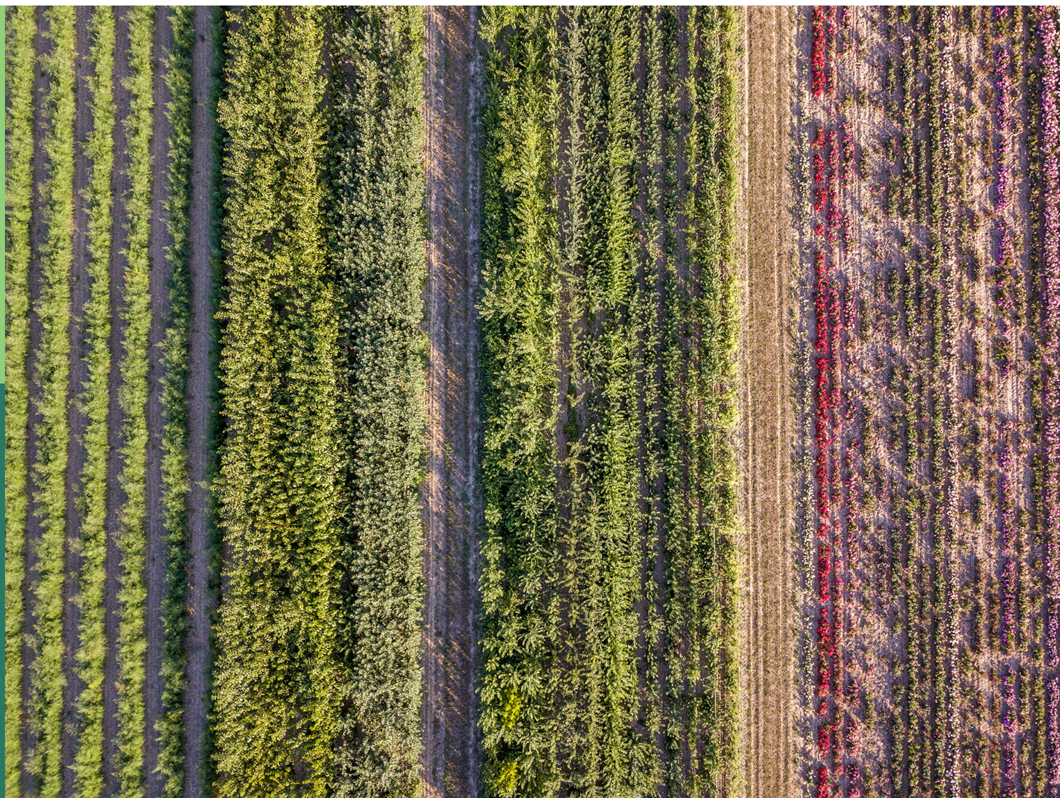

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Evaluating the adoption and impacts of agricultural technologies

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Editorial: Evaluating the adoption and impacts of agricultural technologies

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Editorial on the Research Topic
Evaluating the adoption and impacts of agricultural technologies

The development of innovations in agriculture can contribute to achieving many of the development and environmental goals included in government policy agendas. New agricultural technologies play a key role in enhancing output efficiency, thereby minimizing resource usage, addressing climate change, and fostering socio-economic development by alleviating poverty and hunger, creating the opportunity to allocate resources to other critical areas such as education and health. However, just as important as the development of innovations to achieve development and environmental goals is the adoption of these innovations by users and the environmental conditions. Therefore, understanding the role of users' perspectives on the advantages and drawbacks of agricultural innovations, considering factors like the innovation attributes, potential uses, and costs is vital to assess the success of innovations in assessing and achieving policy objectives. Likewise, environmental conditions including peers' views, government support and communication channels used, play a pivotal role in evaluating and enhancing the success of new technologies.

A total of 12 articles contributed to the Research Topic on *Evaluating the adoption and impacts of agricultural technologies*. The articles included in this topic identify intrinsic and extrinsic factors shaping agricultural innovation adoption, assessing their roles in adopters' decisions and success. Evaluations explore interlinkages to land, livelihoods, gender aspects, the environment and food security. Valuable insights for policy design emerge, recognizing that a need for tailored approaches, as emphasized by Malabayabas and Mishra, Mishra et al., Singbo et al., and Korir et al.. More specifically Malabayabas and Mishra found an inverse relationship between farm size and productivity (IR) in eastern India, moderated by joint farming decision-making. Their study revealed a negative association between joint farming decision-making and rice farm productivity, moderating the positive impact found of new rice variety adoption. Hence, policies supporting non-farm income and joint decision making could enhance productivity. Mohammed and Abdulai examine the impact of extending legume inoculant technology adoption on farmers' efficiency, productivity, and welfare in Ghana. The study reveals that technology adoption is linked to increased yield, revenue, efficiency, and farmers' welfare, emphasizing the importance of investing in research and development for yield-enhancing agricultural technologies in impoverished soil conditions. Additionally, robust extension services are crucial to fully exploit the potential of these new technologies. Mishra et al. also examined the relationship between land size and productivity, but in Ethiopia. The study revealed variations based on data collection method (crop-cut yields or self-reported yields). A significant negative relationship was found between plot size, self-reported yield, and gross revenue, with a greater impact on gross revenue than yields. Conversely, in crop-cut yield, a positive and significant association was observed. The authors emphasize minimizing measurement errors, standardizing measurement units and tools, and addressing imperfections in land, labor, and credit markets. Gender issues associated with technology adoption were explored by Singbo et al. and Arouna et al.. Singbo et al. studied the impact of land-enhancing technology, specifically bio-reclamation of degraded land (BDL), on women farmers in Niger. They found that adopting BDL is linked to increased income, dependent on spatial, economic, environmental, temporal and cultural contexts. Prioritizing BDL implementations in areas with significant degraded farmland and economically vulnerable farmers is recommended for formulating policies addressing food security and poverty alleviation in rural dryland areas. Arouna et al. investigated the impact of adopting an improved parboiling technology on the livelihood of women rice parboilers in Benin. Findings indicate that technology adoption positively influenced women parboilers' rice output rate, income, and food security, while reducing poverty. From a policy perspective, it is crucial to provide training for local fabricators and establish credit options. Martinez et al. studied farmers' dual decisions on adopting improved rice varieties and chemical fertilizers and the consequential impact on crop productivity in Bolivia. They found that partial adoption of rice varieties or fertilizers has no impact on yields, but combining these technologies nearly doubles rice productivity. Promoting integrated packages of agricultural technologies for small farmers in Bolivia, rather than individual technologies, would leverage their complementarity, enhancing rice yields and aiming for self-sufficiency while aligning with regional trends of becoming net exporters in global food system.

Spatial and temporal dynamics in adoption decisions were explored by several authors. Wang et al. study the role of farmers' adoption of hybrid rice varieties in addressing food security in China. The authors found a positive but decreasing effect of the adoption of such varieties on rice production with possible spillover and crowding effects of adoption across provinces, highlighting the importance of appropriate designing of agricultural extension strategies. Korir et al. found that farm location and herd size influence adoption decisions when studying 19 technologies in dairy production systems in Ethiopia. Trust in information from government agencies and sharing knowledge between farmers were found to be key to adopt multiple technologies. The authors recommended tailoring innovation strategies to specific farming community situations. Interestingly, female workers were found to be more likely to adopt multiple technologies. Joshi et al. investigated the dynamics of agricultural technology adoption, rice varietal changes, and shifts in natural resource management and land use in Nepal over 16 years using GPS-determined transects. The strategic utilization of GPS-based methods established a durable database, recording long-term shifts in technology and resource adoption patterns. The study found dominance in old-improved varieties, slow adoption of new rice varieties, and suggested the transformation of agricultural land into real estate could impact food and nutrition security in Nepal.

Tennhardt et al. assessed the importance of value chain factors vs. farmer and farm factors in influencing cocoa farmers' adoption of sustainable practices in Ecuador and Uganda. They explored how value chain factors impact implementation and found their significant role alongside farmer and farm factors. Capacity building and stable relationships were linked to specific practices. However, their potential was found not to be fully exploited, indicating a need for improved knowledge dissemination, addressing inhibitors, and aligning sustainability goals within chocolate company value chain initiatives.

Finally the specific impact of seed costs on adoption was also explored by authors like Yan et al. who studied hybrid rice adoption in southern China. While hybrid rice adoption had a positive effect on yields, it led to a decrease in income due to the cost of the new variety. Agossou et al. found that farmers' decisions on improved kersting's groundnut varieties in Benin and Togo were influenced by market availability, with farmers' willingness to pay ∼15% less than the fixed price set by seed companies.

The collection of articles in this Research Topic makes a significant contribution to the literature on technology adoption in agriculture. This Research Topic emphases the importance of understanding the intricate relationship between innovation adoption and achieving broader development and environmental goals. The studies examine the adoption and impact of agricultural technologies, identifying factors that shape adoption decisions and exploring their roles in success. The insights gained are crucial for policy design, recognizing the need for tailored approaches. Spatial and temporal dynamics, as well as gender considerations, are explored, providing a comprehensive understanding of adoption patterns. The investigation of value chain factors in cocoa farming and the exploration of seed costs' impact on adoption provides additional depth to this Research Topic. Overall, this compilation serves as a valuable resource for policymakers and practitioners seeking effective strategies for technology adoption in agriculture.

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Assessing inverse relationship in joint farm decision-making households: An empirical evidence from Eastern India

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In the eastern India region, due to the dominance of fragmented and smaller land holdings and lack of irrigation facilities, the adoption of green revolution technologies has progressed slowly. Economic growth, income, and land fragmentation have induced families to allocate labor to non-farm jobs. In the absence of male decision-makers, spouses are responsible for making farming-related decisions jointly with their husbands. This study examines the inverse relationship between farm size and rice productivity in joint farm decision-making among married couples. The study uses survey data from four eastern states of India. The finding confirms the inverse relationship between cultivated rice area and rice yields. The inverse relationship holds but weakens when we control for farm and household characteristics and land quality. Smallholders in India tend to have dual employment, and as a result, more farm management decisions are being made jointly with spouses. Findings indicate that joint farming decision-making may have an adverse effect on rice productivity. Socially advantaged farmers have a lower yield. Finally, the study reveals that off-farm income from off-farm employment increases rice productivity. Policymakers can strengthen extension services to disseminate farming knowledge (agronomic practices and technology) to socially disadvantaged farmers and off-farm job opportunities for smallholders.

KEYWORDS

rice varieties, farm size, productivity, spouse, green revolution, soil quality, non-farm income

Introduction

Sustaining food security in developing countries is one of the major roles of smallholder producers[1]. In India, most smallholders are located in rural areas and depend on agriculture as their primary source of livelihood. Among the staple crops, rice is primarily produced by smallholder farmers. Smallholder rice farms comprise 75% of the total rice farms covering 37% of the total rice area [Government of India (GoI), 2016]. The significance of these smallholder rice producers became apparent during the

1 Smallholder less than 1ha [Government of India (GOI), 2020].

height of the Green Revolution in the 1970's, where greater emphasis on crop genetic improvement through plant breeding programs. According to Pingali et al. (2019), Green Revolution technologies were effectively designed and implemented for smallholders. These technologies were scale-neutral, and adequate institutional support was given through input subsidies.

Despite the development of new technologies, rice productivity has witnessed a slow growth rate in recent years compared to the early periods of the Green Revolution (Khush, 1999). This is particularly true for eastern Indian states. In 2015, eastern India accounted for 66% of the total rice area in the country and produced more than half (52 million tons) of India's total rice production [Government of India (GoI), 2016][2]. The eastern region is mainly composed of unfavorable rice areas (rainfed), prone to abiotic stress (flood, drought, and salinity), and low levels of education among farming households. Additionally, the region depends on single cropping during monsoon, a major reason for comparatively low and uncertain yields (Barah and Pandey, 2005). For instance, in 2015, the region's average rice productivity was 2.25 t/ha, well below the national average of 3.35 t/ha [International Rice Research Institute (IRRI), 2019]. Higher rice consumption and lower production growth rates can lead to food shortages. The eastern India region primarily comprises the rural population (80% of the total population), and a high percentage are in poverty [22–35%, Government of India (GoI), 2016]. Thus, a sudden decrease in rice production may substantially reduce food security, loss of livelihood, and higher market prices in the region and India in general.

Another factor affecting the region is non-farm employment. Most farmers have dual employment—farm and non-farm. The non-farm jobs are located in urban and semi-urban areas. The movement from farm to non-farm sectors is further facilitated by government programs like the Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA).[3] As a result, the agricultural sector has witnessed labor shortages, higher farm wage rates, and increased production costs for smallholders (Bhattarai et al., 2014). Secondly, as more male household members (farming decision makers) engage in non-farm employment, anecdotal evidence suggests that spouses make farming decisions jointly. Finally, as Niroula and Thapa (2005) noted, land-related issues (such as the law of paternal land inheritance, lack of progressive tax on inherited land, and underdeveloped land market) such as land fragmentation will continue in India and eastern Indian[4] in particular. However, the importance of small farms in Indian farming cannot be discounted due to high productivity compared to larger farms—also known as the inverse relationship (IR) between farm size and productivity. Additonally, smallholders are the major food producers, and several development organizations have used IR in most development strategies by promoting and supporting smallholder production through land reform laws (IFAD, 2013; Gollin, 2019).

Studies in Indian agriculture show strong evidence of IR between farm size and productivity (Khusro, 1964; Sen, 1964; Rao, 1966; Bhattacharya and Saini, 1972; Srinivasan, 1973; Ghose, 1979). Smallholders are more productive than large farms, suggesting that small farms would help address equity and poverty reduction (Hazell et al., 2010). However, Deininger et al. (2017) point out that land fragmentation beyond the threshold farm size would be detrimental to farm productivity—due to the difficulty of using machines as a substitute for farm labor. Chakravorty et al. (2016) found that an Indian farmer's monthly income with <0.5 ha of land can barely cover monthly expenditures. Thus, understanding the relationship between smallholders' farm size and rice productivity is essential in identifying smallholders' significant constraints in eastern India. Several studies found an inverse relationship between farm size and productivity caused by imperfect factor markets, land quality, and measurement errors. When analyzing the IR at the household level, it assumes that farming decisions (such as selecting crops, technology, and labor) are made by male household heads (Orr et al., 2016). However, gender-differentiated preferences on farming decisions such as crop choice and labor use (Bourdillon et al., 2007) may affect managerial skills and thus crop yields. Joint decision-making is gaining significant traction in the literature (Damisa and Yohanna, 2007; Aregu et al., 2011; Ibrahim et al., 2012). Similarly, it is no surprise that joint farming decision-making is taking roots in India (Paris et al., 2010).

Thus, this study analyzes the relationship between farm size and productivity among rice farmers in eastern India. Specifically, the study examines the impact of joint farm decision-making among married couples on rice productivity. The study uses the 2016 Rice Monitoring Survey, a nationally representative household-level survey by the International Rice Research Institute (IRRI). This study contributes to the literature in two ways. First, the study tests for the IR between farm area and productivity. The common explanations based in the literature (such as market imperfection and soil quality

2 We use 2015 rice statistics here for two reasons. First, these are most recent statistics available to us for the eastern India region. Secondly, we use the 2016 Rice Monitoring Survey conducted by IRRI to test our hypothesis. Thus, we wanted to present rice statistics that was closer to the data collection period.

3 Enacted as the National Rural Employment Guarantee Act of India, 2005 is a public policy in India that pays people to seek employment. The wage rate is higher than the daily wages of agricultural workers [Ministry of Rural Development (MORD), Government of India, 2019].

4 The average farm size in eastern India decreased from 2.03 ha in 1971 to 1.15 in 2010 [Government of India (GoI), 2016].

omission) that support IR will be tested to determine if the same factors explain the existence of IR. Second, the study considers intrahousehold farming decision-making[5] by married couples in analyzing IR between farm size and productivity.

Literature review

The inverse relationship (IR) between farm size and productivity has been one of the recurring topics in rural development, which has sparked the interest of most policymakers and rural development practitioners. The IR phenomenon has been appealing among developing countries, justifying the implementation of land reform programs that promote efficiency and equity among poor farmers (Rada and Fuglie, 2019; Helfand and Taylor, 2021). In India, the existence of IR was first identified by Sen (1962) in defining Indian agriculture using the Farm Management data produced by the Ministry of Food and Agriculture. The author found that increasing farm size reduced farm productivity. The high productivity among small farms could be associated with the intensive use of family labor which assumed no outside employment opportunity resulting in surplus labor. In assessing the profitability in production, the family labor was often valued by imputing the current wage rate, resulting in losses among small farms compared to large farms. Similar findings were found by Khush (1999) using the same data but noticed that the family labor explanation only holds in specific landholding sizes. The author showed that full employment of family labor holds when the landholdings range from 10 acres to 15 acres and hire additional laborers once landholdings go beyond 15 acres. Since there is a threshold of landholdings area, family labor can be fully employed. Indeed, Rao (1966) pointed out that the size of the landholdings cannot be ignored in the analysis because it can affect labor and managerial aspects of production. The author further suggested that mechanization would be the best option for large farms to intensify inputs and avoid managerial difficulties. An additional study by Sen (1966) shows that IR exists due to an imperfect labor market. The Indian peasant farm sector tends to have a labor surplus and wage gap. The wage gap exists when production seasonality and a proposed institutional minimum wage rate exist.

Most of the studies mentioned above depend on aggregated data from the Farmer Management survey, which concludes that an IR exists due to an imperfect labor market. However, aggregated Farm Management data may not necessarily capture the real reasons for the inverse farm-productivity relationship. Rudra (1968) used data from Agro-Economic Research Center, which uses village-level information from Punjab and Uttar Pradesh. The study shows that the intensity of irrigation and inputs used in relation to productivity is constant regardless of the landholding sizes, contrary to the Farm Management data results. A follow-up study by Rudra (1968) analyzed the IR using correlation analysis of 20 villages. The study shows that only two villages show significant and inconsistent results among the villages. Results of one village show that the IR only holds up to 20 acres while the other village shows no systematic pattern. On the other hand, Deolalikar (1981) found that IR exists in India with low agricultural technology and diminishes with farms using a high level of technology.

Several studies used disaggregated data to find alternative reasons to explain the IR phenomenon in Indian agriculture. For example, Saini (1971) analyzed Farm Management data (1954–1957) using the imputed current market wage rate, which explains the profit losses among small farms. The author suggested that instead of using the imputed value of the family labor that leads to market distortion, one should also consider placing a rental value on owned land. Results showed positive profits even in the smallest landholdings when the value of owned land was included in the model. On the other hand, village-level variations can be one of the reasons for IR. For example, Bhattacharya and Saini (1972) included a dummy variable for an Indian village in testing IR. Using data from 1955 to 1968, the authors found that the inverse relationship varies per village. Regarding weather variations, Srinivasan (1973) found out that even though farmers apply the optimal inputs in production, farmers experience yield uncertainties due to weather variations. To capture the full effect of weather on productivity, Srinivasan (1973) suggested dividing the stages of production, such as the early stage (sowing and early growing stage) and the late stage (flowering and harvesting stage).

However, the IR in Indian agriculture mentioned above is based on the pre-Green Revolution period. The period is characterized by underdeveloped areas with diverse climatic conditions, landholding structures, and cropping conditions (Ghose, 1979). In introducing Green Revolution technologies, it is essential to know their impact on small and large farmers since Green Revolution technologies are considered scale-neutral.[6] Saini (1971) pointed out that the IR phenomenon is expected to change or disappear, particularly in Green Revolution areas. Green Revolution technologies require complementary inputs (such as fertilizer and irrigation) to achieve full yield potential. Thus, dependence on purchased inputs and capital goods is easily available for large farmers with access to credit and savings (Heltberg, 1998). Several studies show that Green Revolution's introduction in Asia lessens or removes the IR. For example, Deolalikar (1981) examined the fertilizer application among Indian farms using district-level data. The study found that IR exists when fertilizer is excluded in the estimation and reversed once fertilizer usage intensifies and size increases. The finding

5 Most studies examining intra-household decision-making are from sub-Saharan Africa (SSA) and Latin America.

6 These are technologies that can be divided and distributed at no extra cost (Pingali et al., 2019).

suggests that large farms benefited more from the technological change through fertilizer than small farms. Increased fertilizer use was found to explain the IR among rice and wheat producers (Subbarao, 1983) in eastern India.

However, the study by Bhalla (1979) found that the IR persisted even during the Green Revolution. Larger farms increased their output per acre and proportion of area under modern varieties (MV) due to their accessibility to cheaper credit. In addition, Birthal et al. (2016) examined crop performance in 20 Indian states. The authors found that small farmers benefitted from technological development by allocating more high-yielding crops and applying more fertilizer and pesticides than larger farms. However, the IR is only prominent in high-value crops (e.g., fruits, plantation crops, and sugar crops) than in food crops such as rice and wheat. The high mechanization increased efficiency, particularly among large rice and wheat farmers. A similar explanation was found by Otsuka et al. (2016) regarding the lessening of the farm-size productivity relationship. Otsuka et al. (2016) pointed out that with the development of non-rural farm sectors and increasing wage rates, larger farms prefer to use labor-saving technologies (such as farm machinery), enabling them to be efficient and reverse IR. Despite weakening the farm-productivity relationship in Green Revolution technologies, the standard explanations in the literature that support IR include market imperfection, land quality, intensive production, error in estimation, and household characteristics.

Market imperfection

Market imperfection was identified by Sen (1966) as one of the reasons for the existence of inverse farm size and productivity. An extensive part of literature focused on IR found that the interplay of different sectors causes market imperfections. For example, Feder (1985) pointed out that inverse farm size-productivity exists when imperfect labor, credit, and land markets exist. Interestingly, Lamb (2003) found that when assessing the labor by gender and controlling for village labor and land imperfections, the IR is wholly removed only in male labor demand but not in female labor. This suggests that increasing own production is one way to address market failure in the female labor market. On the other hand, Barrett (1996) found that an IR exists if there are differences in household marketed surplus and price risk-averse farmers. The cost of supervision can also be the reason for IR to exist. For example, Heltberg (1998) found that IR exists where supervision constraints exist since outside labor is an imperfect substitute for family labor. In addition, Feder (1985) pointed out that the efficiency of the hired labor depends on the intensity of the family labor supervision. Deininger et al. (2018) examined the changes in IR in 17 Indian states over 25 years. The authors showed that increasing wages in the 2000's led to more intensive capital, lessening the supervision cost among family labor.

However, IR is not solely explained by market imperfections. Only a small portion of the IR can be explained by the market imperfection when using a yield approach method. For example, Barrett et al. (2010) analyzed 17 villages in Madagascar in 2002, including multi-plot level information, and found IR. The authors note that imperfect markets contribute only one-third of the inverse relationship. The same is true in the study of Ali and Deininger (2015), which found an inverse relationship between farm size and shadow profit when analyzing rural households in several villages in Rwanda. A reversed relationship happens when family labor is valued based on village market rates. On the other hand, a comparison between rice farmers in China and India by Wang et al. (2015) found that land crop yield increases with machine use in both countries. However, there were contrasting results when analyzing the IR. The authors showed that China has a positive plot size-productivity relationship, while India still follows the conventional IR. China's results may be due to the development of the land rental market, family labor outmigration, and high-quality farmland construction policy.[7] However, Assunção and Braido (2007) rejected the market imperfection explanation when plot-level data from India. The IR still exists even after controlling for unobserved household characteristics.

Soil quality

Land quality is another common alternative that most studies used to explain the farm-size productivity inverse relationship. Often, these variables are omitted due to the unavailability of plot-level quality measures. However, given the availability of more plot-level data, several studies included land quality indicators. Bhalla (1988) and Bhalla and Roy (1988) make use of extensive national farm-level data in India with land quality information from the Fertilizer and Demand Survey (FDS) 1975–1976. Results show a negative relationship between land quality and productivity. Bhalla and Roy (1988) added that if the land quality is considered, the IR weakens but still exists. However, Bhalla (1988) also pointed out that although there was an IR when land quality was included, the results may lead to large specification errors if it follows the conventional production function that negligently treats land quality.

Some studies that analyzed the IR also used panel data. For example, Carter (1984) analyzed panel data from Haryana (India) during 1969–1970. The author found that the intervillage soil difference partly explains the farm size-productivity relationship and that small farms are inefficient since they use more inputs than large farms. On the other hand, Lamb (2003) estimated the effect of land quality measures in the IR using

7 This policy encourages farmers to increase operational farm sizes through development of public infrastructure (e.g. irrigation facilities and roads).

panel data by International Crops Research in Semi-Arid and Tropics (ICRISAT), covering several crops. The author used random and fixed effects in estimating the relationship between land quality and profits. The study found that the land quality difference explains the IR between farm size and profits when applying random effects. Aside from soil quality, Assunção and Braido (2007) used longitudinal village-level studies by ICRISAT (1975–1985) and found that IR is also related to land value. However, Barrett et al. (2010) rejected soil quality as the main reason for the IR relationship. The authors show that even if the specific soil quality (e.g., soil carbon, nitrogen, and potassium content, soil pH, clay, silt, and sand shares) was accounted for, the estimation did not suffer from no omitted variable.

Measurement and misspecification errors

Measurement errors that would lead to statistical modeling issues are some of the new evidence challenging the existence of IR. For example, Lamb (2003) found that measurement errors may explain most of the inverse relationship, which is more pronounced when using fixed effects. The author also cautioned researchers in applying fixed-effects models to estimate the relationship between farm size and productivity. Barrett et al. (2010) found the same results when they examined the IR relationship in Madagascar using fixed effects to know if household and village market imperfections trigger the results. They found that imperfect markets only contribute to one-third of the IR. Other literature tries to control for farm attributes to remove the measurement error. For example, Assunção and Braido (2007) control for plot attributes, irrigation status, and land value shows no effect for large farms. In addition, Ali and Deininger (2015) controlled the time-variant and invariant characteristics of the plot (soil quality and unfavorable productivity shocks) in estimating IR. Foster and Rosenzweig (2017) found that area measurement error in Indian farms is small and does not explain the observed. However, most land size information depends on farmers self-reporting land area resulting in imprecise land measurement.

Recent studies use a global positioning system (GPS) to measure land area accurately to remove land area measurement error. GPS estimated land area is becoming popular since it can provide more accurate land measures, particularly in larger household surveys Carletto et al. (2013, 2015). The study by Carletto et al. (2013) shows that using GPS measured area indicated a stronger IR than using the self-reported area in Uganda. In addition, using the self-reported area measure shows that smaller farmers tend to over-report their land size while large farmers underestimate their land resulting in higher yields. Similarly, Desiere and Jolliffe (2018) addressed the measurement error issue using crop cut estimates in Ethiopia. It shows that IR exists using self-reported estimates and disappears when crop-cut area estimates. Carletto et al. (2013) found that overestimating or underestimating farm size drives the IR. Similar results were found by Dillon et al. (2019) when using three land measurement methods (farmer estimates, GPS, and compass-and-rope) that self-reported farm size leads to measurement error (overreporting for small farms and under-reporting for large farms). However, Bevis and Barrett (2019) rejected the measurement error that leads to IR. The author argued that crop yields along the perimeter might be higher than those in the interior due to less competition with nutrients and water, resulting in IR. In the Uganda study, the authors show that the IR disappears after controlling for the perimeter plots.

Farmer related factors

The characteristics of the household have an influence on the IR between farm size and productivity. For instance, Rada and Fuglie (2019) found that agricultural education among small farmers (0–5 ha) in Brazil positively impacts the total production factor by 16%. Carter (1984) argued that found the inverse relationship is not due to sampling bias resulting from farmer literacy but to a mode of production due to intensive use of inputs that generate higher income. Heterogeneity of skills also affects the inverse relationship. Assunção and Ghatak (2003) study shows heterogeneity regarding farmers' skills and imperfect credit market influenced the IR. The authors pointed out that skilled peasants are more likely to become farmers, which entails a higher opportunity cost to be a wage earner than an unskilled peasant.

Some studies attempt to show the existence of IR through an intrahousehold bargaining context. For example, Udry (1996) found that allocating land to women would reduce marginal productivity and suggested reallocating the land to men to increase output. Assunção and Braido (2007) also attempted to study the effect of intrahousehold resource allocation by analyzing managerial resources and crop mix in India. However, the results did not support that intrahousehold issues result in IR. Thus, based on the existing literature, there are mixed explanations for the existence of IR. Most studies assumed that only the household head is responsible for all farming decisions and represents all the household members. In the increasing number of studies about intrahousehold bargaining, each household member may have their preference which can affect the productivity of the household. Though few attempted to incorporate the intrahousehold issues in IR, most failed to explain the relationship. This study will attempt to revisit the IR debate by incorporating a joint farming decision-making strategy among married couples in India.

Theoretical framework

The study's theoretical framework shows the linkage between farm area and productivity, following Assunção and Braido (2007). I assume a Cobb-Douglas production function with household i is expressed as

$$Y_i = A_i T_i^{\alpha_t} K_i^{\alpha_k} L_i^{\alpha_l} \exp(\varepsilon_i) \qquad (1)$$

where Y_i is the yield; T_i is the total cultivated area; L_i and K_i are the amount of labor and non-labor inputs used; A_i represents observable household and land characteristics associated with different factors like village and caste; and ε_i is the error term. It is also assumed that there is constant returns to scale and a competitive market. For the household to know the optimal amount of labor and non-labor inputs, one should solve the profit maximization problem given as

$$\underset{(k\_i,l\_i)}{\max_{T}}\ E\left(a_i\ T_i^{\alpha_i} k_i^{\alpha_i} l_i^{\alpha_i} \exp(\varepsilon_i) - k_i - \ l_i\right) \qquad (2)$$

where $y_i = pY_i$ is the value of the output; $p,\ w,\ and\ r$ are prices of $Y_i,\ L_i,\ and\ K_i$, respectively; $k_i = rK_i$ is the value of the non-labor inputs; $l_i\ =\ wL_i$ is the value of the labor inputs; and a_i is a price adjusted technological term ($a_i\ =\ \frac{A_i}{(r)^{a_i}(w)^{\alpha_i}}$). After solving the maximization problem, the optimal inputs for labor and non-labor inputs would be:

$$k_i^* = T_i\left(\alpha_k^{(1-\alpha_l)} \alpha_l^{\alpha_l} \alpha_i E(\exp(\varepsilon_i))\right)^{\rho} \qquad (3)$$

$$l_i^* = T_i\left(\alpha_l^{(1-\alpha_k)} \alpha_k^{\alpha_k} \alpha_i E(\exp(\varepsilon_i))\right)^{\rho} \qquad (4)$$

where $\rho = \frac{1}{1-\alpha_k-\alpha_l}$

In this analysis, Assunção and Braido (2007) further assume that the yield should be independent of the area of the farm, following the assumption that a_i and error term ε_i and can be written as

$$\frac{y_i}{T_i} = (\lambda a_i)^{\rho} \exp(\varepsilon_i) \qquad (5)$$

where $\lambda = \alpha_k^{\alpha_k} \alpha_l^{\alpha_l} \left[E(\exp(\varepsilon_i))\right]^{(\alpha_k + \alpha_l)}$

Data and methods

Primary data

The study uses the 2016 Rice Monitoring Survey conducted by IRRI. A rice-producing household is defined as a household that produced rice during the past 12 months. The study uses the 2016 Rice Monitoring Survey conducted by IRRI. The survey targeted the rural population of eastern India by randomly selecting rural areas based on the 2011 Census of India. Four states in the eastern part of India are considered for this study: eastern Uttar Pradesh, Odisha, Bihar, and West Bengal. A multi-stage sampling technique was adopted in selecting the respondents. In the first stage, the number of districts was randomly selected in each state using the Census of 2011.[8] On the other hand, the second stage involves determining the number of villages based on the proportion of each state's total rice area, keeping the total number of villages at 720. Among the selected villages, household samples are randomly selected using the household census village data. A total of 101 districts and 1,931 rice-producing households are included in the survey (Table 1).

TABLE 1 Sample districts and smallholder households in eastern India, 2016.

State	Number of districts	Number of households
Eastern Uttar Pradesh	37	513
Odisha	30	627
Bihar	16	329
West Bengal	18	442
Total	101	1,931

Source: 2016 Rice Monitoring Survey conducted by IRRI.

A structured questionnaire was used to interview the household's primary male and female decision-makers. Information regarding household and rice production was collected from male respondents, while information about livestock and household assets were collected from the female respondents. The survey employed male and female enumerators to elicit unbiased responses in the interview process. The male enumerator interviewed the male respondents, while the female enumerator interviewed the female respondents. The study focused on information regarding the 2015 wet season, the primary rice-growing season in eastern India. A computer-assisted personalized interview (CAPI) program, *Surveybe*, was used to collect the data. To capture the joint farm decision-making, the study considered only married couples and simultaneously identified the male and female decision-makers. Choosing the married couple as a major criterion is necessary since it is common for Indian households to have an extended family living in one house. Farmers and spouses were queried about seven farm production-related decisions. For the current study, we only considered joint farm decision-making regarding the selection of rice seed varieties. Thus, the joint farming decision-making takes a value of 1 if the husband and wife made the decision jointly and 0 otherwise.

8 This data set contains information about all the districts, villages, towns, and cities in urban and rural India.

TABLE 2A Summary statistics of the variables used in the estimation, Eastern India, 2016.

	Low ($n = 773$)	Mid ($n = 163$)	High ($n = 995$)	All farms[a] ($n = 1,931$)
Yield (kg/ha)	625.23	1,471.47	2,743.77	1,788.30
Total area (ha)	0.37	0.41	0.45	0.42
Experienced flood/drought 2015 (= 1 if yes; 0 otherwise)	0.65	0.71	0.60	0.63
Total plots	1.18	1.41	1.53	1.38
Share of irrigated land to the total land (%)	47.97	41.24	36.03	41.25
Proportion of medium land	0.63	0.41	0.43	0.51
Land with title (1 = yes; 0 otherwise)	0.75	0.74	0.76	0.76
Seed (kg/ha)	43.32	35.05	34.75	38.21
Total fertilizer (kg/ha)[b]	286.59	290.49	264.23	275.40
Family labor (person-days/ha)	30.22	34.09	32.43	62.13
Hired labor (person-days/ha)	16.93	16.98	14.96	31.68
Contract labor (person-days/ha)	11.82	12.37	16.98	15.92
Total labor (person-days/ha)[c]	58.97	63.44	64.37	14.53
Machine (1 = yes; 0 otherwise)[d]	0.83	0.89	0.88	0.86
Local rice varieties (= 1 if yes; 0 otherwise)	0.18	0.10	0.09	0.12
MRV1 (before 1977) (= 1 if yes; 0 otherwise)	0.16	0.04	0.07	0.10
MRV2 (1977-85) (= 1 if yes; 0 otherwise)	0.19	0.09	0.24	0.21
MRV3 (1986-1995) (= 1 if yes; 0 otherwise)	0.17	0.06	0.06	0.10
MRV4(1996 or later) (= 1 if yes; 0 otherwise)	0.11	0.04	0.07	0.08
MRV5 (hybrid rice 1995 and later) (= 1 if yes; 0 otherwise)	0.05	0.36	0.09	0.10
MRV6 (mixed generation) (= 1 if yes; 0 otherwise)	0.14	0.31	0.40	0.28
Age respondent	47.44	49.01	48.27	48.00
Education respondent	5.57	6.08	5.50	5.58
Household size	3.73	3.69	3.63	3.68
Scheduled castes/tribes[e] (=1 if yes; 0 otherwise)	0.31	0.23	0.29	0.30
Other backward castes[f] (=1 if yes; 0 otherwise)	0.48	0.40	0.34	0.40
General castes (=1 if yes; 0 otherwise)	0.21	0.37	0.36	0.30
Farm located in Bihar (1=yes; 0=otherwise)	0.20	0.41	0.29	0.27
Farm located in Odisha (1=yes; 0=otherwise)	0.36	0.26	0.31	0.32
Farm located in Uttar Pradesh (1=yes; 0=otherwise)	0.30	0.17	0.09	0.18
Farm located in West Bengal (1=yes; 0=otherwise)	0.14	0.17	0.31	0.23
Non-rural farm major source of income[g] (=1 if yes; 0 otherwise)	0.62	0.66	0.74	0.62
Joint farming decision-making[h] (=1 if yes; 0 otherwise)	0.48	0.39	0.45	0.46

[a] Low performing farms (yield <1,297.28 kg/ha); Mid performing farms (yields between 1,297.28 to 1,662.09 kg/ha); and High performing farms (yield greater than 1,662.09 kg/ha).
[b] Total chemical fertilizer used in rice production: NPK- Nitrogen, phosphorus and potassium (15-15-15); DAP - Diammonium Phosphate (18-44-0); And Urea (46-0-0) (www.Yara.com).
[c] This includes family labor, hired labor, and contract labor. Person-days/ha is the same as person-days/ ha in which 6 hours =1 day.
[d] The household is using at least one of the types of machines listed: Tractor, Transplanter, sprayer, combine harvester, thresher, diesel pumps, and electric pumps.
[e] Includes designated groups of historically disadvantaged indigenous people in India. The terms are recognized in the Constitution of India (GoI), and the various groups are designated in one of the categories. since independence, the scheduled castes and scheduled tribes were given reservation status, guaranteeing political representation.
[f] Includes castes that are socially and educationally discriminated.
[g] At least one household member has off-farm labor like salaried job, business, and works in service industry.
[h] Husband and Spouse Are Making Farming-Related Decisions Jointly.
Source: Rice Monitoring Survey 2016.

Table 2A provides the summary statistics of the variables used in the analysis. Due to space and brevity, the definition of the variables is presented in Table 2B. The sample households can be categorized based on the rice productivity: low-performing (yield <1,297.28 kg/ha); mid-performing farms (yields between 1,297.28 to 1,662.09 kg/ha); and high-performing farms (yield >1,662.09 kg/ha). The table shows that more than half of the sample households are high-performing groups, followed by low performing (40%) and mid-performing (8%). Rice yield in the sample has an average of

TABLE 2B Variable definition used in the analysis, eastern India, 2016.

Variables	Definition
Age (years)	The age of respondent (years)
Education level (years)	The years of education of the husband (years)
Household size	Number of adults in the house (16 years and above).
Joint farming decision-making	The participation of men and women: (1) husband and wife jointly participate in deciding the rice variety; (0) men solely decides the rice variety in the presence of the wife.
Land title	Ownership of land based on the name in the land title (certificate).
Caste	These are designated groups of historically marginalized indigenous people in India. The terms are recognized in the Constitution of India (GoI), and the various groups are designated in one of the categories. Since independence, the scheduled castes and scheduled tribes were given reservation status, guaranteeing political representation.
Non-rural farm employment	Number of the household members with off-farm labor like salaried job, business, and works in service industry.
Share of irrigated area	Share of irrigated rice area to the total rice area.
Proportion of mediumland	This is the proportion of area that a farmer considered to be a mediumland to the total rice area.
Experienced flood/drought 2015 (1 = yes, 0 otherwise)	This indicates if the farmer experienced flood, drought, or both in cropping the year 2015
Seeds use (kg/ha)	Seeds use (kg/ha).
Fertilizer use (kg/ha)	Total chemical fertilizer used in rice production: NPK- nitrogen, phosphorus and potassium (15-15-15); DAP - diammonium phosphate (18-44-0); and Urea (46-0-0).
Total plots	Total plots the household is currently cultivating.
Labor	Labor use can be classified as hired labor (person-days/ha); family labor (person-days/ha); and contract labor (person-days/ha). 1 day = 6 h

Source: 2016 Rice Monitoring Survey conducted by IRRI.

1,788 kg/ha, which is lower than the national average of 3,700 kg/ha [International Rice Research Institute (IRRI), 2019]. The dominance of the marginal farms can be observed in the average cultivated area of the whole sample, which reached 0.41 ha. Regarding land ownership, most of the cultivated rice areas in the sample have ownership land titles.

Rice is mainly planted in nearly half of the households' medium part of the land. Among the farm groups, around 62% of these low-performing farms used most of this medium land compared to the other groups. In terms of irrigation, more than 40% of the cultivated rice area is irrigated through supplemental irrigation (such as deep or shallow tube well, canals, and ponds). The low and mid-performing groups have a high percentage of irrigated areas compared to high performing group. This suggests that many farmers still rely on rainfall for water sources. However, rainfed areas are prone to water-related problems like floods and drought, which can be one reason for the slow growth in productivity in the area (Pandey et al., 2007; Dar et al., 2013). In the study done by Gumma et al. (2011), it was estimated that an average of 8–40% and 17–22% of the total rice area in eastern India are prone to flood and drought, respectively. Table 2A shows that 63% of the rice producers in the sample were affected by flood and drought, with mid-performers affected the most.

The major inputs used in rice production are seeds, labor, and fertilizer (NPK, DAP, Urea). The table shows that low-performing farms apply the highest amount of seeds, reaching 43.32 kg/ha. The use of fertilizer is highest in the mid-performing group, which reached 290.49 kg/ha. On the other hand, the labor used in rice production comprises three types: family, hired, and contract labor. Family labor provided the highest day worked on the farm (32 person-day/ha) and followed by contract labor (17 person-day/ha) and hired labor (15 person-day/ha). It also shows that the participation of family labor is constant across the group. Among the farm groups, low-performing groups required the lowest labor in rice production (60 person-day/ ha) compared to the two farm groups.

Table 2A also reveals that nearly half of rice producers use MRV6 (mixed generation) and MRV2 (1977–1985). The farm group shows that almost 71% of low-performing farms still use old rice varieties[9] and local rice varieties. Using these local varieties may explain the low productivity of the group. The study of Bagchi and Emerick-Bool (2012) found that local varieties in West Bengal generate a lower yield than modern varieties by 1.63 kg/ha. It also shows high performing groups preferred the MRV2 (rice varieties released between 1977 and 1985) and MRV6 (mixed). The hybrid rice varieties (MRV5) and MRV6 (mixed) are preferred in the mid-performing group. According to Behura et al. (2012), combining different varieties is one of the practices in flood/drought-prone areas to ensure

9 Old varieties as rice varieties that were released 1995 and earlier which excludes local varieties.

production. This is not surprising since a high percentage of farmers experienced flood/drought during 2015.

It shows that the average operator is 48 years old with an average of 6 years of education in household characteristics. There is also a narrowing difference in education between husband and wife, which increases as productivity increases. However, the age difference is constant across farm groups. Most farmers belong to other backward castes (40%), followed by general caste and scheduled tribe/ caste (30%). Among the farm group, low and mid groups constitute primarily Scheduled tribes/Scheduled castes, while the high-performing group is composed mainly of general castes. In terms of farm location, most of the rice producers are found in Odisha (17%), followed by Bihar (44%), West Bengal (42%), and Uttar Pradesh (39%). More than 60% of the household has at least one member with non-farm employment in terms of sources of income. It shows that high-performing groups have the highest percentage of households with non-rural farm employment. Finally, in deciding on rice varieties, Table 2A shows that nearly half of low and high-performing groups jointly participate in farming decision-making in determining the rice variety.

Empirical strategy

Following a Cobb-Douglas production function, the farm size-productivity relationship is usually tested using an ordinary linear regression (OLS):

$$Y_i = \beta_0 + \delta_1 L_i + \varepsilon_i \tag{6}$$

where i is the ith household; Y is the yield; L is the cultivated land; β is the intercept, and ε is the error term with constant variance and mean zero $\varepsilon_i \approx i.i.d.\ N\left(0, \sigma^2\right)$. Equation (6) is an example of a naïve regression that only includes one independent variable. To know if there is a correlation between the cultivated area and productivity, we can test the null hypothesis $H_0: \delta_1 = 0$ that there is no relationship against the alternative relationship in which there exists an inverse relationship $H_1: \delta_2 < 0$. However, Equation (6) estimates likely to suffer from omitted variables. Thus, we need to estimate a less restrictive model by adding potential explanatory variables. Equation 7 shows an expanded version of Equation (6) where household variables (e.g., age and years of the respondent, family size, non-rural farm income), joint farming decision-making (selecting rice variety), and farm variables (e.g., occurrence stress, percentage of irrigated land, the quantity of seeds, the quantity of fertilizer (NPK), total labor, and rice varieties) were added.

$$Y_i = {x_i}'\beta_2 + \delta_2 L_i + \nu_i \tag{7}$$

where β_2 represents all associations between productivity and vector of household and farm variables; and ν_i an error term. If there is an existence of IR, then we fail to accept the null hypothesis $H_0: \delta_2 = 0$ in favor of the alternative relationship in which there exists an inverse relationship $H_2: \delta_2 < 0$.

Following Gaurav and Mishra (2015) and Barrett et al. (2010), including additional control variables would help me establish the inverse productivity relationship in rice production based on major explanations discussed in the literature, such as household-specific market imperfections and soil quality. The household-specific market imperfections can be one of the reasons for the existence of IR. In this case, shadow prices of inputs (such as land and labor) and outputs often create heterogeneity between households. According to Feder (1985), farm area is correlated to unobserved household-specific shadow prices, which may cause IR. The household-specific variables used are dummies for state and caste where the household belongs. Thus, accounting for the unobserved household-specific market imperfections, the specification becomes:

$$Y_i = {x_i}'\beta_3 + \gamma_3 L_i + \lambda_3 H + \omega_i \tag{8}$$

where λ_3 represents state and caste controls and ω_i is an error term. If the household-specific failure is the reason for an IR, controlling for the household-specific effect (λ_3) would lead to failure to reject $H_0: \gamma_3 = 0$. Soil quality is another standard variable omitted due to data unavailability but is considered one of the major reasons for IR existence. However, Barrett et al. (2010) pointed out that soil quality affects farm size and yield differently, resulting in biased estimates if ignored. To account for this issue, I included the variable proportion of medium land,[10] which can be a proxy for topography. The specification is given as follows:

$$Y_i = {x_i}'\beta_4 + \gamma_4 L_i + \lambda_4 H + \phi_3 Q_i + \eta_i \tag{9}$$

where ϕ_3 is coefficients for soil quality and η_i is the error term.

Results and discussion

Inverse relationship

Table 3 shows the results of the four specifications for testing the relationship between farm size and rice productivity using rice yields (kg/ha): (1) naïve; (2) farm and household factors fixed; (3) household fixed effects; and (4) soil quality fixed effects. Results of the naïve specification (Model 1, Table 3)

10 Rice farms in India can be categorized as upland, medium land, and lowland. The lowlands are located in the lower top sequence of the fields while uplands are located in the upper part of the field with less moisture availability and poor soil quality (sandy soils with less water retention capacity). Lastly, medium land is intermediate between lowland and upland (Gauchan et al., 2012).

TABLE 3 Rice productivity estimation with household-specific and soil quality control, eastern India, 2016.

	Naïve *Model 1*	Farm and Household *Model 2*	Household fixed *Model 3*	Soil quality fixed *Model 4*
Dependent variable: Rice yield (kg/ha), log				
Total area (ha), log	−0.034	−0.221***	−0.113*	−0.110*
	(0.026)	(0.061)	(0.060)	(0.060)
Experienced flood/drought 2015 (=1 if yes; 0 otherwise)		−0.257***	−0.156***	−0.171***
		(0.046)	(0.046)	(0.046)
Share of irrigated land to the total land area (%)		−0.002***	−0.001	−0.001
		(0.001)	(0.001)	(0.001)
Land with title (1=yes; 0 otherwise)		0.0281	−0.018	−0.024
		(0.051)	(0.049)	(0.049)
Seed (kg/ha)		−0.092**	−0.118***	−0.118***
		(0.039)	(0.039)	(0.039)
Total fertilizer[a], log		−0.041	0.0502	0.044
		(0.060)	(0.059)	(0.059)
Total labor[b], log		0.105**	0.029	0.012
		(0.043)	(0.042)	(0.042)
Use machine (1=yes; 0 otherwise)[c]		0.237***	0.103	0.119*
		(0.069)	(0.070)	(0.070)
MRV1 (before 1977) (=1 if yes; 0 otherwise)		0.230**	0.207**	0.222**
		(0.091)	(0.089)	(0.089)
MRV2 (1977-85) (=1 if yes; 0 otherwise)		0.266***	0.245***	0.255***
		(0.077)	(0.074)	(0.074)
MRV3 (1986-1995) (=1 if yes; 0 otherwise)		0.282***	0.478***	0.477***
		(0.091)	(0.089)	(0.089)
MRV4(1996 or later) (=1 if yes; 0 otherwise)		−0.106	0.013	0.018
		(0.095)	(0.094)	(0.093)
MRV5 (hybrid rice 1995 and later) (=1 if yes; 0 otherwise)		0.505***	0.456***	0.454***
		(0.096)	(0.095)	(0.095)
MRV6 (mixed generation) (=1 if yes; 0 otherwise)		0.605***	0.626***	0.615***
		(0.075)	(0.073)	(0.073)
Age respondent, log		−0.006**	−0.004	−0.004
		(0.003)	(0.003)	(0.003)
Years of education respondent, log		−0.019	−0.071	−0.072
		(0.100)	(0.094)	(0.094)
Household size, log		−0.092	−0.031	−0.032
		(0.059)	(0.059)	(0.059)
Non-farm major source of income[d] (=1 if yes; 0 otherwise)		0.179***	0.142***	0.130***
		(0.050)	(0.050)	(0.050)
Joint farming decision-making[e] (=1 if yes; 0 otherwise)		−0.104**	−0.091**	−0.080**
		(0.048)	(0.041)	(0.040)
Controls			−0.056	−0.045
Scheduled castes/tribes[f] (=1 if yes; 0 otherwise)				
			(0.056)	(0.056)
Other backward castes[g] (=1 if yes; 0 otherwise)			−0.150**	−0.143**
			(0.059)	(0.059)
Farm in Bihar (1=yes; 0=otherwise)			0.589***	0.539***
			(0.074)	(0.076)

(Continued)

TABLE 3 (Continued)

	Naïve *Model 1*	Farm and Household *Model 2*	Household fixed *Model 3*	Soil quality fixed *Model 4*
Farm in Odisha (1=yes; 0=otherwise)			0.307***	0.259***
			(0.097)	(0.010)
Farm in West Bengal (1=yes; 0=otherwise)			0.782***	0.731***
			(0.097)	(0.010)
Proportion of medium land				−0.138***
				(0.050)
Constant	7.101***	6.910***	6.597***	6.791***
	(0.039)	(0.451)	(0.454)	(0.457)
β_0= −0.034		17.610***	6.040**	5.810**
Observations	1,931	1,931	1,931	1,931
R-squared	0.001	0.102	0.162	0.166

[a]Total chemical fertilizer used in rice production: NPK- nitrogen, phosphorus and potassium (15-15-15); DAP - diammonium phosphate (18-44-0); and Urea (46-0-0) (www.yara.com).
[b]This includes family labor, hired labor, and contract labor. Person-days/ha is the same as person-days/ha in which 6 h =1 day.
[c]The household uses at least one of the types of machines listed: tractor, transplanter, sprayer, combine harvester, thresher, diesel pumps, and electric pumps.
[d]At least one household member has off-farm labor like salaried job, business, and works in the service industry.
[e]Husband and spouse are making farming-related decisions jointly.
[f]Includes designated groups of historically disadvantaged indigenous people in India. The terms are recognized in the Constitution of India (GoI), and the various groups are designated in one of the categories. Since independence, the scheduled castes and scheduled tribes were given reservation status, guaranteeing political representation.
[g]Includes castes that are socially and educationally discriminated.
Source: 2016 Rice Monitoring Survey conducted by IRRI.

show a negative but insignificant relationship between cultivated rice area and rice productivity. The estimate suggests that doubling the cultivated rice area decreases rice yield by 3%. However, the above estimate only predicts a 0.1% variation in rice yields, and the estimates may be more likely to suffer from omitted variables bias. Model 2 (Table 3) includes farm and household characteristics variables in the empirical estimation. The coefficient of cultivated rice area (farm size) is negative and statistically significant at the 1% level of significance. The estimate suggests that doubling the cultivated rice area decreases rice yield by 22%. Notice that the estimates, in absolute terms, increased and became significant in Model 2 than in Model 1 (Table 3). Our estimate between farm size and yields is higher (22% vs. 10%) than those obtained by Desiere and Jolliffe (2018).

Additional variables in Model 2 (Table 3) show that major inputs like total labor, use of machines, and modern rice varieties, compared to local rice varieties, increase rice yields in the sampled four states of India. For instance, Model 2 shows doubling labor use increases rice productivity by 10 percent. On the other hand, the coefficient of rice seeds is negative and significant at the 5% significance level. This finding is consistent with Mishra et al. (2015), who found a negative and significant relationship between the quantity of seeds and rice output in Bangladesh. However, the above finding contrasts with Mishra et al. (2018) and Mariano et al. (2011), who found a positive and significant relationship between the quantity of seeds and rice output. In sum, the above findings reveal that rice farmers in the four states can increase rice productivity by lowering the amount of rice seeds and raising labor and machinery usage on their farms. Regarding the household variables, Model 2 (Table 3) shows that having non-farm employment income increases rice yields. Thus, income from non-farm sources could help smallholder families to relax their credit constraints.[11] Additional income from non-farm employment could be used for farm investments (buying land machinery etc.), additional inputs, quality inputs, and new technology, thus increasing rice productivity. Our finding is consistent with Evans and Ngau (1991), who found a positive relationship between off-farm participation and agricultural investment.

The coefficient of joint farming decision-making is negative and statistically significant at the 1% level of significance. The coefficient is also significantly negative in Models 3 and 4. Result suggests that farming decisions made jointly in married farm households negatively affect rice yields. A plausible explanation could be untimely, miscommunication, and missing information when making the final decision. For example,

11 Rizov et al. (2001) note that in transitional economies off-farm income may be more important than farm assets in reducing capital constraints.

decisions may change if the conditions on the ground change, and the spouse cannot get in touch with the farmer—thus using her capabilities to pivot. Another reason, as pointed out by Acosta et al. (2020), is the perception of joint decision-making in farming.[12] The authors test gender differences in perceptions of joint decision-making in farming in Uganda. Decisions like 'what and where to plant' and 'to sell land' were more frequently perceived as joint by women than men. Indeed, Mottaleb et al. (2017) argue that women like the intrinsic qualities of rice varieties (e.g., taste, cooking qualities, and grain shape) more than those with the highest yield. Our findings underscore the importance of rice quality when farmers choose rice variety, especially during the joint-decision-making process.

Following Barrett et al. (2010) and Gaurav and Mishra (2015), two common explanations for IR are household-specific market imperfections and soil quality. Our study addresses market imperfections by including household-specific fixed in Model 3. Model 3 of Table 3 shows that IR still holds, and the coefficient of farm size is negative and statistically significant at the 10 percent level of significance. Testing the joint household-specific controls shows significant ($p = 0.000$ at the 1% level of significance), thus rejecting the null hypothesis ($H_0 : \lambda_3 = 0$). The magnitude of the farm area coefficient, compared to Model 2, also decreased by almost half. Our finding is consistent with Barrett et al. (2010), showing that controlling for household-specific weakens the explanation of the existence of IR. Model 4 (Table 3) shows the results when soil quality control when included in the estimation. Again, the coefficient of farm size is negative and statistically significant at the 10 percent level of significance. Testing the joint soil quality specific controls shows significant ($p = 0.000$ at the 1% level of significance), thus rejecting the null hypothesis ($H_0 : \lambda_4 = 0$). Also, the magnitude of the coefficient, in absolute terms, is similar to Model 3. The inclusion of soil quality controls decreased the magnitude of the coefficient of farm area (cultivated rice area) by nearly half as compared to Model 2. Our finding is consistent with Bhalla and Roy (1988) regarding the weakening of the relationship when controlling for land quality. The authors argued that ignoring the land quality may result in specification errors, leading to an artificial impact on productivity.

Overall, the inputs show almost identical signs and significance in the three models (Model 2, 3, and 4) in Table 3. The occurrence of flood and drought has a negative and significant impact on rice productivity in the three models. However, the magnitude of the coefficient (in absolute terms) decreases once more controls are included in the empirical model. The adverse effect of flood and drought on rice yields is consistent with Mishra et al.'s (2015) findings, who found that abiotic stresses (drought and flood) reduced rice production among rice farmers in Bangladesh. Thus, controlling for soil quality seems to emphasize the effect of flood and drought. In terms of caste, households belonging to other backward castes (OBC) have a negative impact on rice yield when added to the model. This finding is not surprising because OBC's farms are usually located in poor water conditions, prone to flooding, lower land fertility, and low productivity. Additionally, farmers from socially disadvantaged castes like OBCs, have a lower probability of accessing farming information, public extension services, and inferior resource endowments. Our finding is consistent with Dar et al. (2013).

12 Alwang et al. (2017) found that men claimed sole responsibilities over the decisions while the spouses claimed the decisions were made jointly.

Conclusion and policy implications

Smallholders are one of the major players in the Indian rice sector. With the continuously increasing number of small and fragmented land, inevitably, this sector will remain. However, with the slow growth in rice production for the past decades in India, understanding the relationship between smallholders and rice productivity is essential in identifying the major constraints. The existence of IR in farm size and productivity is a common justification for implementing land reform programs that promote efficiency and equity among poor farmers. Hence, this paper analyzed the farm size and productivity relationship among rice farmers in eastern India. Specifically, the study focused on how intrahousehold joint farming decision-making impacted rice productivity. The study used the 2016 Rice Monitoring Survey, a nationally representative household-level survey by the International Rice Research Institute (IRRI). The current study showed two significant findings. First, the study found an inverse relationship (IR) between farm size and rice productivity, and the IR weakens when controlling household effects and soil quality. Second, the study provided evidence of joint farming decision-making on rice productivity. The study found that joint farming decision-making had an adverse impact on rice productivity, at least in the sampled rice farms in eastern Indian states of Uttar Pradesh, Bihar, Odisha, and West Bengal.

There are several implications of this study. First, the existence of IR among the smallholder does not warrant land reform programs. Instead, policymakers should focus on policies addressing the causes of structural land fragmentation, including policies for enhancing the rural infrastructures, modifying inheritance laws, and reviewing land reform enactments. Secondly, policymakers need to provide greater support to small farms. Policymakers need to focus efforts on improving crop production, yield, farm investment, and extension services. Thirdly, since the joint farming decision-making in choosing the rice variety penalizes rice productivity, enhancing the couple's knowledge regarding rice varieties should be a priority for policymakers, researchers, and extension agents. Broadcasting information about rice variety characteristics (planting duration, pest resistance, and ecosystem) and consumer traits (aroma, grain length, and taste) should be in order. The couples could help develop new rice varieties by providing rice breeders information on their preferred rice traits through Participatory Varietal Selection (PVS). A PVS study by Manzanilla et al. (2014) regarding submergence tolerant varieties in Southeast Asia shows that female farmers are as knowledgeable as male farmers in evaluating the lines/variety visible characteristics.

Fourth, developing a robust private farm machinery market with private entrepreneurs can support the demand and supply of farm machinery. In fact, rice farming at a smaller scale could be achieved by hiring machinery services. Fifth, to support marginalized and socially disadvantaged farmers government can engage in information and technology diffusion and farming practices through extension agents and other agricultural advisory services. To this end, the government can use Krishi Vigyan Kendra or Agricultural Science Center) to provide agricultural extension services to reach not only socially disadvantaged farmers but smallholders in rural India.

Lastly, findings underscore the non-farm sector's importance in increasing rice yields. As a result, government policies that influence general economic conditions profoundly impact smallholder households. Policies aimed at increasing off-farm job opportunities should be enacted carefully. Off-farm employment opportunities require higher human capital. Policymakers can facilitate access to education and job opportunities is of paramount importance in determining off-farm employment and the transformation of smallholder agriculture.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found at: https://doi.org/10.7910/DVN/0VPRGD.

Author contributions

Conceptualization, statistical data analysis methodology and investigation, and writing—original draft preparation: MM. Writing—review and editing, supervision, and project administration: AM. Both authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Impacts of extension dissemination and technology adoption on farmers' efficiency and welfare in Ghana: Evidence from legume inoculant technology

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Examining the welfare impact of agricultural development interventions that incorporate diffusion of improved production technologies to farmers within extension delivery programs can be very challenging, because of the difficulty in disentangling the individual impacts of the production technology and the extension delivery program. Using recent farm level survey data from extension dissemination program of legume inoculant technology of 600 farmers in Ghana, we employ a recent methodological approach to investigate, simultaneously, the impact of the inoculant technology adoption and the extension program participation on farmers' productivity, efficiency and welfare. We decompose each of these impact measures into subcomponents whose causal paths can be traced to both the adoption of the production technology and the extension delivery program. We find that, in terms of yields and net revenue, direct contribution of improved technology adoption alone is 34 and 64%, respectively, and 35 and 66% indirectly due to improved farmer efficiency, leading to 36 and 74% improvement in farmers' welfare, respectively. On the other hand, direct contribution of extension delivery program participation alone is 66 and 36%, respectively, with 66 and 34% indirectly due to improved farmer efficiency, resulting in 64 and 26% improvement in farmers' welfare, respectively. Based on the findings, we recommend that policymakers should invest in research and development to produce yield enhancing agricultural technologies suitable for poor and degraded soil conditions in developing countries which can contribute immensely to poverty and food insecurity reduction. The development of new agricultural technologies must be pursued with vigorous provision of extension services to farmers to be able to exploit the full potentials of the new technologies.

KEYWORDS

mediation analysis, treatment effect, impact assessment, legume inoculant technology adoption, stochastic frontier analysis

Introduction

The increasing global food demand calls for adoption of new agricultural technologies to increase food production. Similar concerns in the past led to the introduction of the green revolution, a policy that advocated for intensifying the use of high yielding varieties, mineral fertilizers and tractors among smallholder farmers in developing countries (Pingali, 2012). Although the policy led to an increase in agricultural productivity and food supply, it also contributed to worse environmental impacts such as degraded lands and impoverished soils (Pingali, 2012; Zhang et al., 2015). Increase in food production cannot be achieved without sufficient nitrogen supply, as nitrogen allows farmers to increase crop production per unit area of land (Zhang et al., 2015). To mitigate the effect of pollution from reactive nitrogen while ensuring sufficient food production, a new paradigm shift is required (Mutuma et al., 2014; Zhang et al., 2015).

The Integrated Soil Fertility Management (ISFM) is one of such new approaches employed to promote soil fertility enhancing technologies for resource-poor farmers in developing countries (Crowley and Carter, 2000). A technology promoted under the program among smallholder soybean farmers in northern Ghana is the legume inoculant technology. Soybean is targeted due to its potential to undergo sustainable intensification, its industrial value and nutritional quality (Foyer et al., 2018; van Heerwaarden et al., 2018). The inoculant technology is an organic input containing isolates of an elite strain of bacterial (*Bradyrhizobium* spp.) and organic carrier material (Lupwayi et al., 2000). The inoculant technology is seen as cost-effective alternative to rehabilitating poor soils by enhancing the build-up of biological nitrogen fixation (BNF) organisms in the soil (Giller, 2001). Evidence of the potential productivity gains from inoculant has been documented in the literature (e.g., Rurangwa et al., 2018; van Heerwaarden et al., 2018; Mohammed and Abdulai, 2022). Notably, grain yield of soybean from inoculated fields increased by 20–29% in Mozambique (Chibeba et al., 2018) and 12–19% in the northern region of Ghana (Ulzen et al., 2016), relative to uninoculated fields. Yield response to inoculant significantly varies across agro-ecological zones in Africa and depend on agronomic practices and varietal promiscuity to the strain of the *Rhizobia* in the inoculant (van Heerwaarden et al., 2018). To improve efficiency, organizations involved in the dissemination of the inoculant technology employ several innovative extension methods[1] to train farmers on good agronomic and crop management practices on the inoculant technology. However, the important issues that require investigations are: to what extent has the inoculant or the extension improved the efficiency of farmers, and differential impacts of the inoculant and extension provision on efficiency improvement, as well as the impact of the efficiency gain on farmers' welfare. Our goal in this study is to simultaneously assess the impact of the inoculant technology adoption and the extension participation on farmers' productivity and efficiency. Usually, agricultural development programs such as the inoculant dissemination program often have dual goals of inducing an upward shift in the production frontier and the promotion of better management practices, which incorporates two potentially endogenous treatments in a single program (Bravo-Ureta, 2014). That is, treatment of farmers to new superior technology and the building of human capital, each having the potential to influence both the technology frontier function and the inefficiency function independently (Huang and Liu, 1994; Kumbhakar and Tsionas, 2009).

However, empirical studies often overlook the double treatment endogeneity, most often addressing one of them, and subsuming the other into distributional assumptions of the model. For instance, in Dinar's et al. (2007) study on the impact of extension services in Greece, extension participation is analyzed as performing a dual role, an input in the production function and a factor narrowing the technology gap, exerting direct and indirect effects in the production process. Their approach implicitly assumed homogeneous technology and fail to account for selection bias in the extension participation. In the event that farmers self-select into an extension program or adopt a superior production technology, the direct and indirect effects due to heterogeneity in technology or enhanced farmer capacity will be unaccounted for and the full impact will be miss measured. Other studies following the seminal work of Dinar et al. (2007) employed a mixed multi-stage approach to address the issue of selectivity and technology heterogeneity (e.g., Bravo-Ureta et al., 2012, 2020; Villano et al., 2015; Abdulai and Abdulai, 2016; De los Santos-Montero and Bravo-Ureta, 2017; Abdul-Rahaman and Abdulai, 2018). Even though the mixed multi-stage approach accounts for selection bias, it fails to account for the direct and indirect impacts that heterogeneous production technologies may have on both the production frontier and the efficiency function. The mixed multi-stage approach also attempts to address technology heterogeneity among production units by estimating group-specific frontiers for different groups of production units and further use the group frontiers to obtain the meta-frontier for comparison. However, because the maximum likelihood estimates of the predicted group-specific frontier is neither known a prior nor estimated relative to the same frontier, some degree of biasness in this approach is unavoidable and difficult to ascertain (Huang et al., 2014). Moreover, as indicated by Triebs and Kumbhakar (2018), the approach subsumes observed variables like extension service with the potential to augment the farmer's managerial

1 The extension channels employ are video documentaries, radio listening clubs, on-farm and off-farm trials, field days, brochures, use of community volunteers.

ability in the inefficiency parameter of the model. On the contrary, the managerial ability does not only influence the inefficiency function but also the technology frontier, resulting in non-neutrality of the production function (Huang and Liu, 1994; Triebs and Kumbhakar, 2018). Also, the endogeneity issues addressed in the mixed multi-stage approach center mainly on the feedback between the technology choice and the production model residuals, but not on accounting for endogeneity, which could separately and simultaneously affect the technology frontier and the production inefficiency function (Chen et al., 2020).

The present study attempts to fill the gap and contribute to the above literature on impact assessment and technical efficiency, using survey data of 600 farm households from northern Ghana. Specifically, we employ the stochastic frontier model with endogenous treatment and mediator effect (Chen et al., 2020), to estimate the impact of dual purpose development interventions, and to decompose the impact into direct and indirect effects. This recent approach brings together mediation analysis[2], treatment effect and that of the stochastic frontier models in a single framework.[3] Using this approach, we are able to disentangle the dual purpose inherent in agricultural development interventions' impact into four components. That is, the direct effects on the technology frontier, the indirect effects on the technology frontier that go through the mediator, the direct effects on the technical inefficiency, and the indirect effects on the technical inefficiency that go through the mediator. Our approach departs from the conventional approaches in the literature (e.g., Bravo-Ureta et al., 2012, 2020; Villano et al., 2015; Abdulai and Abdulai, 2016; De los Santos-Montero and Bravo-Ureta, 2017), in which a conventional SPF (stochastic production frontier) model that corrects for sample selection bias is estimated. In particular, we estimate a treatment effect model using the stochastic frontier regression framework, while addressing endogeneity from selection bias, endogenous treatment and mediator variables. We also account for treatment heterogeneities among production units. An important requirement for successful implementation of this approach is the existence of good and valid instruments for identifying both the mediation and the treatment effects, something that may be considered a limitation, just like any instrumental variable approach.

2 The mediation analysis is also known as the Baron and Kenny (1986) models in the applied statistics literature.

3 Caveat: please note that the approach employed in this paper is not a conventional production function, rather, a combination of mediation and treatment effect analysis, and therefore relaxes the stringent assumptions underpinning conventional production functions approach.

The rest of the paper is organized as follows: In Sections Conceptual and empirical framework and The identification strategy, we present the conceptual and empirical framework and empirical identification of causal impact, respectively, Section Empirical specification and estimation discusses the empirical specification and the estimation procedure, while Section Study area, data and descriptive statistics describes the data and descriptive statistics. The Empirical results and the Conclusions and policy implications are presented in the last two sections.

Materials and methods

Conceptual and empirical framework

In agriculture, new production technologies such as high yielding varieties and complementary inputs like fertilizer (or as in our case, the legume inoculant technology) have the potential to shift the production frontier upwards (Huang and Liu, 1994; Kumbhakar and Tsionas, 2009; Triebs and Kumbhakar, 2018). Also, farmers who receive extension services or technical training on the new technology may experience further shift in the production frontier upwards by reducing production inefficiencies (Mohammed and Abdulai, 2022a). The two shifts involve two potentially endogenous treatments in a single agricultural development intervention that incorporates dissemination of new production technologies and training of farmers. First, adoption of a new superior technology that affects both the production frontier function and the inefficiency function (Kumbhakar and Tsionas, 2009), and second, extension training that builds human capital with the potential to influence both the production frontier function and the inefficiency function (Huang and Liu, 1994; Triebs and Kumbhakar, 2018).

To represent both frontiers, let Y denote individual farmer i observed output under a given production technology and X be a vector of observed covariates. We express the farmer's observed output in a conventional stochastic frontier form (Kumbhakar and Lovell, 2000) as;

$$Y = Y^{*} - u, \quad u \geq 0 \tag{1}$$

where Y^{*}, is the unobserved stochastic frontier that may be influenced directly by the new technology and indirectly by extension training, and $u \geq 0$, is the unobserved production inefficiency assumed to be randomly distributed, which may also be influenced directly by extension training and indirectly by the new technology. The expression in Equation 1 indicates that Y^{*} and u are two distinct unobserved random components, which can be separately identified. In line with Chen et al. (2020), we stochastically express each unobserved function in terms of observed covariates[4] in a system of equations as follows;

$$Y = \begin{cases} Y^* = h\left(X,\ \beta^h\right) + v \\ u = g\left(X,\ \beta^g\right) + \tilde{u} \end{cases} \quad and \tag{2}$$

$$E\left[Y^*|X\right] = h\left(X,\ \beta^h\right)\ and\ E\left[u|X\right] = g\left(X,\ \beta^g\right),\ E\left[v|X\right] = 0,\ E\left[\tilde{u}|X\right] = 0$$

where X is a vector of covariates, $h(.)$ is the frontier function with parameter vector β^h and $g(.)$ is a non-negative inefficiency function with parameter vector β^g, while v and $\tilde{u}$ are error terms assumed to be independently and identically distributed. $E[.]$ is the expectation operator which identifies the conditional mean expectations of the equations in the system. To relate the effect of the production frontier and the inefficiency to observed farmer-specific potential outcome, given his observed characteristics and inputs, we express Equation 1 in terms of its conditional mean representation in Equation 2 as follows;

$$E\left[Y|X\right] = h\left(X,\ \beta^h\right) - g\left(X,\ \beta^g\right) \tag{3}$$

By letting Y_1 to be the potential outcome of a farmer who adopts the technology (i.e., the inoculant technology) and Y_0 be the potential outcome, if the same farmer did not adopt, then, the average treatment effect on the treated (ATT) for adopters can be specified as;

$$ATT = E\left(Y_1 - Y_0|D = 1\right) = E\left(Y_1|D = 1\right) - E(Y_0|D = 1) \tag{4}$$

where D is a binary adoption indicator, with $D = 1$ if the farmer adopts and $D = 0$, otherwise.

The identification strategy

In observational data situation like ours, evaluating the impact of the inoculant dissemination program on farmers' welfare and the shifts in the production technology and inefficiency functions may suffer serious identification problems, resulting in biased estimates. However, with the availability of good and valid instruments, it is possible to categorize the whole population into well identified mutually disjoint sub-population of adopters who are compliers of the instruments (Imbens and Angrist, 1994; Angrist et al., 1996).

In our setting, we use rural electrification as the most likely exogenous instrument that can identify various sub-population of inoculant adopters. Given that the *rhizobia* in the inoculant survive within a temperature limit of about 25°C, it requires a controlled temperature storage facility. Hence, it is expected that farmers who live in communities connected to the national grid of electricity supply may have easy access to the technology, compared to their counterparts who live in communities without electricity supply. If we let Z_1 represent an instrumental variable (IV) that takes a value of 1, if the farmer's village is connected to national electricity grid, and 0 otherwise, the propensity of a farmer adopting the technology can be specified in a latent variable adoption decision model (i.e., D^*) as follows:

$$D^* = \gamma_{z_1} Z_1 + \gamma_x X + U_D,\ \ with\ D = \begin{cases} 1, & if\ D^* \geq 0 \\ 0, & otherwise \end{cases} \quad \text{and}$$
$$D = 1(\gamma_{z_1} Z_1 + X\gamma_x + U_D \geq 0) \tag{5}$$

where D is a discrete adoption decision indicator, with $D = 1$ if the farmer adopts the inoculant technology and 0 otherwise, X is a vector of covariates, γ is the parameter of interest and U is the error term.

Naturally, it is expected that the effect of extension service participation, which improves the managerial skills of the farmer, is mainly observed after the farmer adopts the technology on which the extension training is based on. That is, when the farmer uses or adopts the inoculant technology. As such, extension functions as a post-adoption mediator and can be modeled as a function of adoption. With a potentially endogenous binary mediator, such as the extension service participation in this case, the mediation effect can be identified with a continuous exogenous variable with known distribution and whose level differs with adoption status (Frölich and Huber, 2017; Chen et al., 2020). In this circumstance, we rely on farmer's distance to the nearest extension office as a possible exogenous continuous instrument. We expect that farmer's propensity to participate in extension service programs would increase as the distance decreases and then decrease as the distance increases. If we let Z_2 be a continuous instrumental variable (IV) whose distribution[5] and level decreases as mediation takes the value of 1, and increase as mediation goes to 0, then, the propensity of a farmer to participate in the extension program and also adopt the technology can be expressed in a latent variable mediation model (i.e., M^*) as follows:

$$M^* = \alpha_d D + \alpha_{z_2} Z_2 + X\alpha_x + U_M,\ with$$
$$M_i = \begin{cases} 1, & if\ M^* \geq 0 \quad \text{and} \\ 0, & otherwise \end{cases}$$
$$M = 1(\alpha_d D + \alpha_{z_2} Z_2 + X\alpha_x + U_M \geq 0) \tag{6}$$

4 The frontier $h(.)$ and the inefficiency $g(.)$ functions allow for same or different covariates in both functions, however, for notational convenience, we use a general X.

5 See Figure A1 in the Supplementary material for the plot of the distribution of the continuous IV Z_2, showing both properties of increasing and decreasing propensities, as a necessary condition for identification.

where M is a binary mediation indicator, with $M = 1$ if the farmer participates in the extension program and 0 otherwise, D is the adoption status indicator, X is a vector of covariates, α is the parameter of interest and U is the error term. Considering Equations 5 and 6, (which identify both the potentially endogenous adoption and extension decisions), the post-mediation potential outcome Y is a function of D and M, assuming that the post-mediation potential outcome can be represented as $Y(D, M(D))$, where $M(D)$ is the mediator function, whose effect depends on the adoption status of the farmer.

Given a binary adoption indicator [i.e., D(1), D(0)] and a binary IV ($Z_1 \in \{0,1\}$), four potential outcomes representing four mutually disjoint sub-population of farmers can be identified as follows (Imbens and Angrist, 1994; Angrist et al., 1996);

$$(D(1), D(0)) = \begin{cases} (1,1), & \textit{always takers}, \\ (1,0), & \textit{compliers } (\mathbf{C}), \\ (0,1), & \textit{defiers}, \\ (0,0), & \textit{never takers}. \end{cases} \tag{7}$$

where **C** is an indicator of instrument compliers, who are induced to adopt the technology based on the instrument. It is assumed that a randomly chosen farmer in the complier sub-population, no matter the circumstance, does not change adoption status other than the assigned status by the instrument (Angrist et al., 1996). Due to this known property of the compliers, their potential impact better approximates that of causal estimates from a full compliance experimentation. Therefore, by conditioning on the observed covariates X and the complier status **C** of the farmers, the average treatment effect on the treated as expressed in Equation 4 can be identified (Chen et al., 2020) as follows:

$$\begin{aligned} CLATE &= E[Y(1, M(1)) | X = x, \mathbf{C}] \\ &\quad - E[Y(0, M(0)) | X = x, \mathbf{C}] \end{aligned} \tag{8}$$

where *CLATE* is the conditional local average treatment effect. Also, because the levels of the continuous instrumental variable for identifying the mediation effect varies with adoptions status, it is possible to decompose the unconditional local average treatment effect into direct and indirect effects as in Chen et al. (2020):

$$CDLATE = E[Y(1, M(1)) | X = x, \mathbf{C}] - E[Y(0, M(1)) | X = x, \mathbf{C}] \tag{9}$$

$$CILATE = E[Y(0, M(1)) | X = x, \mathbf{C}] - E[Y(0, M(0)) | X = x, \mathbf{C}] \tag{10}$$

where *CDLATE* is the conditional direct local average treatment effect and the *CILATE* is the conditional indirect local average treatment effect. Conversely, the unconditional average treatment effect can also be derived from the conditional local average treatment effects, by conditioning on only the sub-population of farmers who are compliers as follows;

$$\begin{aligned} LATE &= E\left[CLATE(X) \middle| \mathbf{C}\right] = E[Y(1, M(1)) | \mathbf{C}] \\ &\quad - E[Y(0, M(0)) | \mathbf{C}] \end{aligned} \tag{11}$$

$$DLATE = E[Y(1, M(1)) | \mathbf{C}] - E[Y(0, M(1)) | \mathbf{C}] \tag{12}$$

$$ILATE = E[Y(0, M(1)) | \mathbf{C}] - E[Y(0, M(0)) | \mathbf{C}] \tag{13}$$

where LATE is the local average treatment effect which captures the total effect, while DLATE and ILATE are direct and indirect local average treatment effects respectively, that capture the impact due to the adoption of a superior technology and mediation role of extension participation.

Empirical specification and estimation

A farmer's propensity to participate in extension services (i.e., the potential mediation model) may correlate with his inoculant adoption decision (i.e., the potential treatment model) either due to observed or unobserved factors. We assume that the error terms are independently and identically distributed and follow a bivariate normal distribution. In line with Chen et al. (2020), we specify the joint extension participation and inoculant adoption decisions as a bivariate probit model, with a bivariate normal distribution and CDF $F_{U_{M,D}}(.,., \rho_{md})$ as follows:

$$\begin{aligned} &P(M, D | Z_1, Z_2, X, \eta), \text{and} \\ &\begin{bmatrix} U_M \\ U_D \end{bmatrix} | (Z_1, Z_2, X) \sim N\left(\begin{bmatrix} U_M \\ U_D \end{bmatrix}, \begin{bmatrix} 1 & \rho_{md} \\ \rho_{md} & 1 \end{bmatrix} \right) \end{aligned} \tag{14}$$

where $\eta \equiv (\alpha_d, \alpha_{z_2}, \alpha_x, \gamma_{z_1}, \gamma_x, \rho_{md})$ is a maximum likelihood estimator of a vector of parameters. In a first-stage estimation, a bivariate probit model is estimated to control for selection bias from both observables and unobservables. To unify the impact assessment and mediation analysis within the stochastic frontier analysis framework, we represent the frontier function of Aigner et al. (1977) and Meeusen and van den Broeck (1977) in the form of Chen et al. (2020), for $d, d' \in \{0,1\}$[6], as follows:

$$\begin{aligned} Y\left(d, M\left(d'\right)\right) &= \breve{h}\left(d, M\left(d'\right), X, \beta^h_{dj}\right) \\ &\quad - \breve{g}\left(d, M\left(d'\right), X, \beta^g_{dj}\right) + U_Y(v\left(d, M\left(d'\right)\right) \\ &\quad + \tilde{u}\left(d, M\left(d'\right)\right)) \end{aligned} \tag{15}$$

6 The observed binary adoption decision indicator d varies as d', taking the value of 1, if a farmer adopts the inoculant technology and 0, otherwise.

where $\breve{h}\left(d, M\left(d^{'}\right), X\right)$ and $\breve{g}\left(d, M\left(d^{'}\right), X\right)$ are potential frontier and non-negative potential inefficiency functions, respectively; X is a vector of covariates; β is a parameter of interest; while $v\left(d, M\left(d^{'}\right)\right)$ and $\tilde{u}\left(d, M\left(d^{'}\right)\right)$ are potential random error terms. The binary adoption indicator is $D = d, d^{'} \in \{0, 1\}$ and $j = M\left(d^{'}\right)$ is the mediator function whose distribution varies with adoption status. The conditional mean expectation of Equation 15 combines the potential outcome and mediator models as;

$$E\left[Y(d, M\left(d^{'}\right)) \,|X, \mathbf{C}\right] = h_{d^{'}}\left(X, \alpha_m, \beta^h_{dj}\right) - g_{d^{'}}\left(X, \alpha_m, \beta^g_{dj}\right)$$

and (16)

$$E\left[v\left(d, M\left(d^{'}\right)\right)\middle|X, \mathbf{C}\right] = 0, E\left[\tilde{u}\left(d, M\left(d^{'}\right)\right)\middle|X, \mathbf{C}\right] = 0, \text{and } E[M\left(d^{'}\right) |X, \mathbf{C}] = m_{d^{'}}(X, \alpha_m)$$

where $m_{d^{'}}(.)$ is a non-negative function of the potential mediator model in {0, 1} with a parameter vector α_m. To reflect variations in the distribution of the non-negative potential mediator model, as the adoption indicator takes the value within {0, 1} in the estimated parameters of interest, we rewrite Equation 16 as follows:

$$E\left[Y(d, M\left(d^{'}\right)) \,|X, \mathbf{C}\right] = h_{d^{'}}\left(X, \alpha_m, \beta^h_{d1}, \beta^h_{d0}\right) - g_{d^{'}}\left(X, \alpha_m, \beta^g_{d1}, \beta^g_{d0}\right) \quad (17)$$

We estimate the parameters in Equation 17 using a two-stage weighted non-linear least squares (WNLS) method[7]. Let the individual farmer's observed outcome (Y), extension service participation (M), inoculant adoption (D) and covariates (X) be a weighted random vector $W \equiv (Y, M, D, X)$ with sample size N, and $\beta_d \equiv (\beta^h_{d1}, \beta^h_{d0}, \beta^g_{d1}, \beta^g_{d0})$ be an arbitrary vector space of a weighted non-linear least squares estimator (WNLSE) observed as $b_d \equiv (b^h_{d1}, b^h_{d0}, b^g_{d1}, b^g_{d0})$. The parameter space can be expressed as the minimizer of the weighted mean square error (MSE) of the observed outcomes of interest (Frölich and Huber, 2017; Chen et al., 2020), which we expressed as follows;

$$\beta_d \equiv \arg\min_{b_{d\in\beta\, d}} \sum\nolimits_{d^{'}=0,1} E[w(d, d^{'}, \alpha_w)(Y - h_{d^{'}}\left(X, \alpha_m, b^h_{d1}, b^h_{d0}\right) + g_{d^{'}}(X, \alpha_m, b^g_{d1}, b^g_{d0}))^2] \quad (18)$$

7 The two-stages are: in the first-stage, the adoption and the mediation [i.e., d and $M\left(d^{'}\right)$] decisions are jointly estimated via a recursive binary probit model to obtain the propensities, conditional on the instrument compliance status, for a farmer to receive adoption and mediation. In the second-stage, the predicted propensities are used to construct the weights use to estimate the potential outcomes via a WNLSE.

where $w\left(d, d^{'}, \alpha_w\right) \equiv w(1{,}1, \alpha_w)$, $w(1{,}0, \alpha_w)$, $w(0{,}1, \alpha_w)$, and $w(0{,}0, \alpha_w)$ is a weighted function of (D, Z_1, Z_2, X), with a parameter vector α_w obtained from the first-stage estimation. The weighting function $w(d, d^{'}, \alpha_w)$ accounts for heterogeneities within the production units that may be due to observed and unobserved firm-specific factors influencing production (or outcomes, which in our case is yield and farm net returns). The WNLS is estimated using the generalized method of moment (GMM) approach. The generalized moment-based approach overcomes the restrictive imposition of distributional functional form assumptions on traditional parametric family of production functions (e.g., Cobb-Douglas, Translog, and others) (Giannakas et al., 2003; Vidoli and Ferrara, 2015; Ferrara and Vidoli, 2017; Ferrara, 2020).

Study area, data and descriptive statistics

The study area is Northern Ghana. Prior to this study, the Northern Ghana constituted three regions namely; Northern, Upper East and Upper West regions. However, following the creation of new regions by the Government of Ghana in 2019, the Northern Ghana currently constitutes five regions, which include Northern, North-East, Savanna, Upper East and Upper West regions. Specifically, the study area was in the former Northern region. The northern region comprises twenty-six (26) districts, of which the study sampled eight (8) districts, in order to conduct a survey for this study (see Figure 1 for Map of study area northern region and the sampled districts). The region covers an area of about 70,384 square kilometers and is considered the largest region in Ghana in terms of land mass. The Northern region shares boundaries with the Upper East and the Upper West regions to the north, the Brong-Ahafo and the Volta regions to the south, Togo to the east, and Cote d'Ivoire to the west. The Black and White Volta Rivers and their tributaries such as the Nasia and Daka rivers drain the region [Ghana Statistical Service (GSS), 2013].

The climate of the region is relatively dry, with a single rainy season that begins in May and ends in October. The amount of rainfall recorded annually varies between 750 millimeters and 1,050 millimeters. The dry season starts in November and ends in March/April with maximum temperatures occurring toward the end of the dry season (March–April) and minimum temperatures in December and January. The harmattan winds, which occur from December to early February, have considerable effect on temperatures in the region, making them vary between 14°C at night and 40°C during the day. Humidity is very low, aggravating the effect of the daytime heat. The main vegetation is grassland, interspersed with guinea savannah woodland, characterized by drought-resistant trees [Ghana Statistical Service (GSS), 2013].

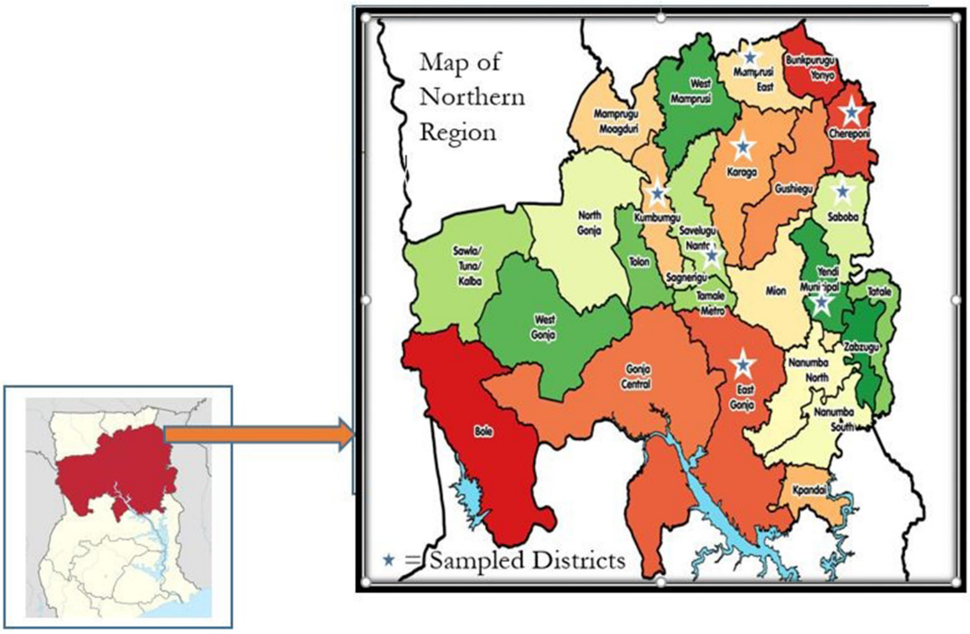

FIGURE 1
The map of study area.

The main occupation of the people in the region is agriculture (70.6%), who live in predominantly rural areas. Degradable soil conditions present major challenge to food productivity and farm livelihoods in the area. To maintain the productive capacity of soils in the region, scientific research organizations such as the International Institute of Tropical Agriculture (IITA) and the Council for Scientific and Industrial Research-Savannah Agricultural Research Institute (CSIR-SARI) and their partner organizations introduced the *Rhizobia* inoculant technology to smallholder grain legume farmers. The inoculant technology is an organic input containing isolates of an elite strain of bacterial (*Bradyrhizobium* spp) and an organic carrier material (Lupwayi et al., 2000). The inoculant technology is seen as a cost-effective alternative to rehabilitating poor soils by enhancing the build-up of biological nitrogen fixation (BNF) organisms in the soil (Giller, 2001). The inoculant technology is also expected to sustainably increase smallholder farmers' productivity, while minimizing cost of production, compared to inorganic inputs such as mineral fertilizers, which is sometimes priced out of reach for most smallholder farmers.

The inoculant dissemination program was centered in the three regions (Northern, Upper East and Upper West) of northern Ghana, due to their soybean production potential in the country as well as the high incidence of extreme poverty situation in these parts of the country. The northern region is second poorest (30.7%) region in the country in terms of extreme poverty incidence followed by the Upper East region (27.7%), with the Upper West region (45.2%) ranking first in the country [Ghana Statistical Service (GSS), 2018, 2019]. With soybean being a cash crop, it is expected that increase in productivity will lead to increase in the household income, which can contribute to poverty reduction for the poor households who depend on agriculture for income as well as food and nutrition security.

The present study uses farm level data obtained from the survey conducted in the northern region of Ghana from June to August 2018. The sample was drawn using a multi-stage sampling technique. Based on the proportion of beneficiary communities (78%) in the inoculant dissemination program and intensity of soybean production in Ghana, northern region was purposively selected. Cluster sampling technique was used to zone the region into two clusters, consisting of eastern corridor zone (ECZ) and western corridor zone (WCZ). Based on dissemination program participation status of districts and intensity of soybean production at the district level within the clusters, eight (8) districts, comprising four (4) from each cluster were purposively sampled. From the ECZ: Yendi, Saboba, Chereponi and Karaga districts were selected, while in the WCZ: East Mamprusi, East Gonja, Savelugu and Kumbungu districts were selected. In consultation with the field officers and agriculture extension agents (AEAs) in the selected districts, 5–7 communities were proportionally sampled, based on the extension channel received, dissemination program participation, and farmer population. One farmer-based organization (FBO) was randomly selected from a list of FBOs that were exposed to the inoculant technology and another randomly selected from a list of unexposed FBOs for each community. Using a lottery approach, we randomly drew five farmers from each FBO. After a preliminary interview session with each of the selected farmers, using a computer assisted personal interview (CAPI), a list of the farmers' information network members (INMs) was compiled. The CAPI random number generator then used farmers' unique identification numbers to randomly sample three network members from each farmer's INMs for interview. A total of 600 farm households, consisting of 325 inoculant exposed farmers and 275 unexposed farmers, were interviewed in a face-to-face session. The data collected include inoculant adoption status, dissemination program participation status, household demographic characteristics, location characteristics, input used, crop yield and farm net returns, plot level precipitation and soil quality.

Definitions and summary statistics of the variables used in the empirical analysis are presented in Table 1. It shows that 54% of our sampled farmers participated in the inoculant extension program. Table 1 also shows that 51% of farmers adopted the inoculant with an average yield of 830 kg/ha soybeans and net returns of 840 GHC/ha.

As shown in Table 1, average land cultivated to soybeans is 5 ha, using an average total labor supply of 8 persons hours per day/ha and 4 kg/ha of agrochemicals (e.g., weedicides) in the process. It further shows that 57% of the farmers are located in the western corridor zone. Table 1 again, shows that 51% of the farmers live in communities that are connected to the national grid of electricity supply, and located at an average distance of 19 km to the nearest extension office and 2 km to the nearest market. In terms of inoculant knowledge test score, Table 1 reveals that farmers obtained an average of 56% inoculant knowledge score from participating in the dissemination program. A comparison of mean differences show some significant differences in observed characteristics between inoculant adopters and non-adopters (see Table A1 in Supplementary material).

On the socioeconomic characteristics of farmers, majority (71%) of the farmers in our sample are males with an average age of 42 years and about 23% attaining at least 1 year of schooling, which seems to be quite low.

Results and discussions

Empirical results

First, we discuss the results of the first-stage bivariate probit model estimates, as the identification of the outcome model hinges on the first-stage estimates. However, we present the estimates from the first-stage in the Table A2 in Supplementary material due to space limitation.[8] Next, we present and discuss estimates of the weighted non-linear least-squares, estimated *via* the generalized method of moments procedure.

First-stage bivariate probit estimates

Table A2 in Supplementary material presents estimates from the bivariate probit model. The model is used to account for selection bias and for identification of the instrumental variable (IV) regression. Table A2 in Supplementary material shows that, both the extension participation model (i.e., the mediation model) and the adoption model are highly correlated due to unobserved heterogeneities. The p-value for the null hypothesis shows that ρ_{md} is significantly different from zero (at 1% level), indicating that farmers' extension participation and inoculant adoption decisions may be correlated due to unobserved heterogeneities. However, the sign for ρ_{md} is negative, suggesting that farmers are likely to substitute adoption of new technologies (such as the inoculant) with knowledge acquisition from extension participation (Huth and Allee, 2002; Mohammed and Abdulai, 2022b). This observation is intuitive, because both extension services and adoption of improved technologies tend to enhance farmers' production efficiency (Abdulai and Huffman, 2000; Kumbhakar and Tsionas, 2009; Triebs and Kumbhakar, 2018). The statistical significance of ρ_{md} also suggests that farmers may have self-selected into the extension program or adoption of the inoculant technology.

Table A2 in Supplementary material also shows that, the two instrumental variables are both statistically different from zero (significant at 1% level). In particular, distance to the nearest extension office (Z_2), which is used to identify extension program participation, is negative and significant at 1% level, suggesting that a decrease in distance to the nearest extension office by 4.3 km, increases the probability of farmers' extension participation. More importantly, farmer's community connection to the national electricity grid (Z_1), which we used to identify the inoculant adoption model, is positive and highly significant at the 1% level. This implies that a one percent increase in rural electrification of communities, increases the likelihood of inoculant adoption by 319%. Intuitively, this makes sense, because the rhizobia used in formulating the inoculant survive in a particular temperature range (25°C), which stands to reason that, communities with access to constant electricity supply could well operate cold storage facilities. As a result, farmers in such communities may have easy access to the inoculant, hence, are more likely to adopt, compared to farmers living in communities without constant

8 Although the covariates in the bivariate probit model can be considered as determinants of inoculant adoption and extension participation, we focus on its identification properties, because the primary interest in this study is for proper model identification, and not to model determinants of participation and adoption decisions.

TABLE 1 Definition and summary statistics.

Variable	Definition	Mean	SD	Min	Max
Outcomes					
Yield	Soybean yield per hectare (lnKg/ha)	829.64	888.24	32.41	5703.87
Farm net returns	Gross revenue less variable cost (lnGHC/ha)	840.26	762.11	75.11	4229.89
Treatment variable					
Adopt-Inoculant	1 If farmer adopts inoculant, Otherwise = 0	0.510	0.500	0	1
Mediator variable					
AES-Part	1 If farmer participated in dissemination program, Otherwise = 0	0.542	0.499	0	1
Production inputs					
Land	Area of land planted with soybean (ha)	5.045	4.371	5.045	4.371
Labor	Total labor used in soy cultivation (Worker-days/ha)	7.808	24.23	0.198	274.73
Agrochem	Total amount of active ingredient in chemical used (kg/ha)	4	7.186	0	87.22
Chemdumy	1 If farmer uses agrochemical, Otherwise = 0	0.025	0.156	0	1
Improvar	1 If farmer uses improve seed variety, Otherwise = 0	0.700	0.459	0	1
Creditconst	1 If farmer is not credit constrained, Otherwise = 0	0.828	0.377	0	1
Farmer-specific characteristics					
Age	Age of farmer (years)	41.56	13.32	18	87
Gender	1 If farmer is male, 0 for female	0.708	0.455	0	1
Edu	Farmer has at least one year of schooling (0–1)	0.227	0.142	0.048	1
Location					
WCZ	1 If farmer is in Western Corridor Zone, Eastern Corridor Zone = 0	0.567	0.496	0	1
Distmarket	Distance to nearest market (km)	2.362	4.137	0.100	50.10
Soilqual	1 If soil quality is good, Poor soil quality = 0	0.508	0.500	0	1
Rainfall	Amount of rainfall in (%)	61.63	16.24	20	100
Instrumental variables					
Distextoff (Z_2)	Distance to nearest extension office in (km)	18.90	25.10	0.016	160.93
Electgrid (Z_1)	1 If community is connected to the national grid for electricity supply, Otherwise = 0	0.512	0.500	0	1
Other control variables					
Testscore	Inoculant knowledge test score (%)	56.091	23.75	2	98
Resemtech	1 If inoculant usage resembles existing inputs usage, otherwise = 0	34.933	35.22	0	100
Techdiff	1 If inoculant application process is considered difficult, otherwise = 0	0.278	0.267	0	1
Dislang	1 If dissemination language is in farmer's mother tongue, otherwise = 0	0.695	0.461	0	1
Comextoff	1 if community has extension agent, otherwise = 0	0.625	0.485	0	1

SD, standard deviation; Min and Max, minimum and maximum values respectively.

electricity supply (Dzanku et al., 2020). Our finding of positive effect of community electricity connectivity on farm households' production activities is consistent with the existing literature on rural electrification impact on households' economic activities (see Cabraal et al., 2005; Independent Evaluation Group-World Bank, 2008; Thomas et al., 2020).

The validity of the instrument for identification of local average treatment effect in our IV regression estimation strategy requires that the instrument be a monotonic increasing function of the level of the instrumental variable (Z_1), and the level of the treatment (D) (see Chen et al., 2020). As shown in Table A2 in Supplementary material, the coefficients of both the instrument (Z_1) in the treatment model and the treatment indicator D in the mediation model have positive signs and are highly significant (at 1% conventional level), suggesting that our instrument is valid and strong. This also implies that inoculant adoption increases with increasing extension participation and community electricity connectivity.

Determinants of technology and inefficiency frontiers

Tables 2, 3 present factors that affect the production technology and inefficiency frontiers with respect to yield (lnKg/ha), for the case scenario that farmers adopt the inoculant technology with mediation (i.e., Adopters^{M}) and the counterfactual scenario of non-adoption with non-mediation (i.e., Non-adopters^{M}), respectively (see Tables 4, 5, for that of farm net returns). The factors explain the observed yield and net returns variabilities in each scenario among farmers with different adoption and mediation conditions in our sample. For the sake of brevity, we focus the discussion on the yield, which can be extended to that of the net returns.

The model estimated is a weighted non-linear least-squares regression using generalized method of moment. In particular, it does not represent any specific conventional production function model, and as such does not depend on any functional form distribution assumptions. Though we estimate a non-linear regression model with some of the covariates being logged, the parameter estimates can be interpreted as in a linear regression estimation (Chen et al., 2020). Our approach of estimating the stochastic production frontier is akin to that of the generalized additive models (GAMs) approach, that fits a response variable on a sum of smooth functions of explanatory variables in a regression context with normal distribution (Ferrara and Vidoli, 2017; Ferrara, 2020). This specification is preferred to the conventional functional form specifications, due to its flexibility in relaxing the need to impose strict linearity and monotonicity condition on the underlying stochastic frontier function between the explanatory variables and the outcomes of interest (Ferrara, 2020).

Each table contains two columns corresponding to two different adoption scenarios. In Table 2, column one contains estimates for the case scenario that a farmer participated in the extension program and also adopted the inoculant technology (i.e., Adopters^{M}), henceforth, mediated-adopters (MA), while column two represents the counterfactual case scenario, if the same farmer had neither participated in the extension program nor adopted the inoculant technology, referred to as non-mediated-non-adopters (NM-NA). In Table 3, column one represents the case scenario that a farmer adopted the inoculant technology without participating in the extension program (i.e., Adopters^{N}), hereafter, non-mediated-adopters (NM-A), whereas column two represents the counterfactual case, if the same farmer had participated in the extension program but did not adopt the inoculant technology (i.e., Non-adopters^{M}), hereafter refer to as mediated-non-adopters (M-NA).

TABLE 2 Adoption with mediation—(weighted nonlinear least-squares)—yield (lnKg/Ha).

Variables	**Adopters^{M} (d, M(d$'$)) = (1,1) Coeff. (S.E)**	**Non-adopters^{N} (d, M(d$'$)) = (0,0) Coeff. (S.E)**
Age	−0.030* (0.018)	−0.052 (0.119)
Agesq	0.0004** (0.0002)	0.001 (0.001)
Gender	0.416*** (0.123)	0.037 (0.301)
Edu	0.618* (0.360)	0.029 (1.547)
lnland	1.596*** (0.140)	1.115*** (0.399)
lnlabor	−0.128*** (0.063)	0.160 (0.200)
lnagrochem	−0.415*** (0.087)	−0.338 (0.221)
Chemdumy	−0.490 (0.206)	3.696 (2.324)
Improvar	0.345*** (0.122)	1.008*** (0.314)
WCZ	0.362*** (0.122)	1.226*** (0.308)
Distmarket	−0.004 (0.015)	0.058 (0.043)
Soilqual	0.236*** (0.167)	0.460 (0.442)
Rainfall	0.003 (0.003)	−0.012 (0.011)
Creditconts	−0.106 (0.113)	1.768*** (0.599)
Tsresid	−0.490*** (0.150)	2.997*** (1.198)
Const.	4.568*** (0.488)	219.307*** (38.043)
Inefficiency		
$\beta^{g}{}_{(ts)}$	−2.355*** (0.431)	0.011*** (0.003)
$\beta^{g}{}_{(0)}$	0.248 (0.188)	5.594*** (0.181)
Observ. (N)	*306*	*294*

***, **, and * are 1, 5, and 10% level of significance; Values in brackets are bootstrapped robust standard errors. Columns one and two represents farmers who participate in the extension program and adopt the inoculant [i.e., Adopters^{M} = mediated-adopters, abbreviated as (MA)] and farmers who neither participate nor adopt the inoculant [i.e., Non-Adopters^{N} = Non-mediated-non-adopters, abbreviated as (NM-NA)], respectively. βg(0) represent estimates of the non-negative inefficiency parameter vector that did not aontrol for farmer inculant knowledge test score and βg(t) represent estimates of the non-negative inefficiency parameter vector that controlled for farmer inculant knowledge test score.

The coefficient of the constant terms in Table 2 that captures the effect of unobserved farmer-specific characteristics are positive and statistically significant, suggesting that unobserved characteristics (such as farmers' inert abilities) may have contributed positively in enhancing farmers' ability to push the production frontier upward, irrespective of the superiority of the production technology employed or extension participation status. Similar positive and statistically significant trend is observed in Tables 3–5.

The results also show that observed farmer-specific characteristics such as education, gender and age have significant impact in shifting the production frontier of farmers. In particular, coefficient of education is positive for all farmers, but statistically significant at 10% level for only MA farmers, suggesting that an increase in education pushes the production

TABLE 3 Adoption without mediation—(weighted nonlinear least-squares)—yield (lnKg/Ha).

Variables	Adopters^{N} (d, M(d$'$)) = (1,0) Coeff. (S.E)	Non-adopters^{M} (d, M(d$'$)) = (0,1) Coeff. (S.E)
Age	−0.108 (0.081)	0.589*** (0.194)
Agesq	0.001 (0.001)	−0.006*** (0.002)
Gender	−0.692*** (0.278)	−1.338 (0.824)
Edu	0.034 (1.834)	0.457 (3.552)
lnland	0.874*** (0.368)	1.507* (0.851)
lnlabor	0.207 (0.163)	0.070 (0.590)
lnagrochem	−0.004 (0.273)	0.217 (0.622)
Chemdumy	−1.981 (8.740)	−1.154 (5.106)
Improvar	0.195 (0.320)	−2.592* (1.419)
WCZ	0.017 (0.358)	−2.525*** (0.870)
Distmarket	−0.019 (0.018)	0.040 (0.097)
Soilqual	0.559* (0.323)	0.885 (1.187)
Rainfall	−0.017** (0.008)	0.060* (0.033)
Creditconts	0.780* (0.415)	−1.797*** (0.735)
Tsresid	−0.307*** (0.099)	−2.450*** (0.791)
Const.	10.159*** (2.344)	−10.378 (7.887)
Inefficiency		
$\beta^{g}{}_{(ts)}$	−0.901*** (0.303)	−6.037*** (1.256)
$\beta^{g}{}_{(0)}$	0.730*** (0.301)	−8.573*** (0.808)
Observ. (N)	*306*	*294*

***, **, and * are 1, 5, and 10% level of significance; Values in brackets are bootstrapped robust standard errors. Columns one and two represents farmers who did not participate in the extension program but adopt the inoculant [i.e., Adopters^{N} = Non-Mediated-Adopters, abbreviated as (NM-A)] and farmers who participate in the extension program but did not adopt the inoculant [i.e., Non-Adopters^{M}, abbreviated as M-NA)], respectively. βg(0) represent estimates of the non-negative inefficiency parameter vector that did not aontrol for farmer inculant knowledge test score and βg(t) represent estimates of the non-negative inefficiency parameter vector that controlled for farmer inculant knowledge test score.

TABLE 4 Adoption with mediation—(weighted nonlinear least-squares)—farm net returns (lnGHC/Ha).

Variables	Adopters^{M} (d, M(d$'$)) = (1,1) Coeff. (S.E)	Non-adopters^{N} (d, M(d$'$)) = (0,0) Coeff. (S.E)
Age	0.007 (0.017)	−0.346*** (0.146)
Agesq	−8.83e−06 (0.0002)	0.004*** (0.002)
Gender	−0.212** (0.096)	0.346 (0.422)
Edu	0.311 (0.259)	3.029 (3.355)
lnland	1.213*** (0.123)	1.903*** (0.615)
lnlabor	−0.060 (0.046)	0.154 (0.275)
lnagrochem	−0.115* (0.068)	−0.860*** (0.364)
Chemdumy	−0.263 (0.155)	−7.137 (5.148)
Improvar	−0.318*** (0.110)	−0.604 (0.545)
WCZ	−0.328*** (0.082)	−0.453 (0.406)
Distmarket	0.021** (0.010)	−0.109** (0.055)
Soilqual	0.229*** (0.078)	2.312*** (0.582)
Rainfall	−0.005*** (0.003)	−0.024 (0.016)
Creditconts	0.047 (0.100)	2.955*** (0.972)
Tsresid	−0.530*** (0.127)	−4.183*** (1.246)
Const.	5.248*** (0.481)	256.133*** (75.911)
Inefficiency		
$\beta^{g}{}_{(ts)}$	−3.990*** (0.688)	−0.015*** (0.003)
$\beta^{g}{}_{(0)}$	0.165 (0.128)	5.737*** (0.304)
Observ. (N)	*306*	*294*

***, **, and * are 1, 5, and 10% level of significance; Values in brackets are bootstrapped robust standard errors. Columns one and two represents farmers who participate in the extension program and adopt the inoculant [i.e., Adopters^{M} = Mediated-Adopters, abbreviated as (MA)] and farmers who neither participate nor adopt the inoculant [i.e., Non-Adopters^{N} = Non-Mediated-Non-Adopters, abbreviated as (NM-NA)], respectively. βg(0) represent estimates of the non-negative inefficiency parameter vector that did not aontrol for farmer inculant knowledge test score and βg(t) represent estimates of the non-negative inefficiency parameter vector that controlled for farmer inculant knowledge test score.

frontier of this category of farmers upwards. Also in Table 2, gender (i.e., being a male farmer) has positive coefficient across all farmers, but statistically significant at 1% level for only MA farmers, suggesting that being a male farmer within our study area generally improve ones' productivity. This observation may be due to the fact that male farmers in most parts of developing countries have better access to family labor, extension service, quality land and other resources than female farmers, a finding that is in line with, Gebre et al. (2019) in their study on gender differences in agricultural productivity among maize farmers in Ethiopia. However, in Table 3, the coefficient of gender is negative for all farmers, but significant at 1% level for only NM-A farmers, suggesting that for female farmers with less access to extension services and quality land, adoption of the inoculant will greatly improve their productivity. The reverse is observed for the net returns in Tables 4, 5, suggesting that in terms of net returns, both male and female farmers are able to push their net returns frontier upwards.

Table 2 also shows that among the conventional inputs (land, labor, agrochemicals and improved seed variety), land has the highest effect on the production frontier. The coefficient of land is positive and statistically significant at 1% level across all farmers, suggesting that farm size has positive effect in pushing the production frontier of both MA and NM-NA farmers upward. Similar positive effect is observed in Tables 3–5.

The coefficient of improved seed variety in Table 2 is positive and statistically significant for all farmers, suggesting that availability of improved crop varieties have positive effect on pushing the production frontier upwards for all category of farmers. However, low quantity of agrochemicals usage, in particular, during weed control may have significant (at 1% level) negative effect in shifting the production frontier of farmers downwards, which could

TABLE 5 Adoption without mediation—(weighted nonlinear least-squares)—farm net returns (lnGHC/Ha).

Variables	Adopters^{N} (d, M(d$'$)) = (1,0) Coeff. (S.E)	Non-adopters^{M} (d, M(d$'$)) = (0,1) Coeff. (S.E)
Age	−0.029 (0.052)	−0.287* (0.169)
Agesq	0.0003 (0.001)	0.003** (0.002)
Gender	0.388** (0.190)	0.365 (1.150)
Edu	0.583 (1.135)	1.314 (6.820)
lnland	1.646*** (0.264)	3.341*** (1.248)
lnlabor	−0.070 (0.111)	−1.081* (0.604)
lnagrochem	−0.383* (0.213)	−1.550* (0.888)
Chemdumy	−0.054 (2.044)	−11.586 (26.093)
Improvar	0.066 (0.196)	−0.173 (1.276)
WCZ	0.363* (0.218)	−2.687*** (0.948)
Distmarket	−0.027*** (0.011)	−0.032 (0.104)
Soilqual	0.441** (0.198)	−3.430*** (1.106)
Rainfall	−0.005 (0.005)	−0.019 (0.036)
Creditconts	0.501* (0.277)	−8.537*** (1.674)
Tsresid	−0.177*** (0.232)	−9.153*** (2.004)
Const.	5.461*** (1.426)	103.102** (54.629)
Inefficiency		
$\beta^{g}{}_{(ts)}$	−1.630*** (0.487)	−0.078** (0.042)
$\beta^{g}{}_{(0)}$	0.296 (0.215)	4.765*** (0.600)
Observ. (N)	*306*	*294*

***, **, and * are 1, 5, and 10% level of significance; Values in brackets are bootstrapped robust standard errors. Columns one and two represents farmers who did not participate in the extension program but adopt the inoculant [i.e., Adopters^{N} = Non-Mediated-Adopters, abbreviated as (NM-A)] and farmers who participate in the extension program but did not adopt the inoculant [i.e., Non-Adopters^{M}, abbreviated as M-NA)], respectively. βg(0) represent estimates of the non-negative inefficiency parameter vector that did not aontrol for farmer inculant knowledge test score and βg(t) represent estimates of the non-negative inefficiency parameter vector that controlled for farmer inculant knowledge test score.

subsequently occasioned significant revenue losses as seen in Tables 4, 5.

In addition to the conventional and farmer-specific characteristics, we also controlled for environmental and geographical factors using zonal dummies, plot level soil quality and precipitation. The results in Table 2 reveal that the zonal dummy which indicates whether the farmer is located in the western corridor zone (WCZ) or eastern corridor zone (base category) is positive and statistically significant at 1% for all farmers, indicating that inoculant adoption and extension participation have positive effects in shifting the production frontier of farmers located in the western corridor zone upward, compared to farmers in the eastern corridor zone. Tables 2, 3 also reveal that soil quality at the farm level has positive effect (statistically significant at 1 and 10% levels, respectively) in shifting the production frontiers upwards for MA and NM-A farmers. However, the positive effect may erode due to insufficient precipitation at the plot level, leading to significant (at 5% level) shift in the production frontier downwards for NM-A farmers and subsequent loss of revenue as shown in Tables 4, 5.

In the last two rows of Tables 2, 3, we present estimates of post-mediation factor(s) that influence farmers' level of (in)efficiency in the usage of the inoculant technology that could have great impact on yields obtained from adoption. We conducted an inoculant technical knowledge quiz and used the test scores to proxy the post-mediation factors in the inefficiency frontier function.

In Tables 2, 3, the coefficient of a constant only inefficiency frontier model [represented as $\beta^{g}_{(0)}$] is positive for all farmers, but statistically significant at 1% level for NM-NA and NM-A farmers only, suggesting that adopting the inoculant technology without sufficient technical knowledge on its usage makes farmers highly inefficient and less beneficial.

On the other hand, the coefficient of the inefficiency model, with inoculant knowledge test score [represented as $\beta^{g}_{(ts)}$] is negative and statistically significant at 1% level for all category of farmers, except for NM-NA farmers, indicating that adopting the technology with sufficient technical knowledge increases farmers' production efficiency (Dzanku et al., 2020). Similar results pattern is obtained for net returns in Tables 4, 5.

Impact of mediation and inoculant adoption on productivity, efficiency and welfare

In this section, we report estimates of the treatment effects derived in Equations 11–13. The results for yields and net returns are presented in Tables 6, 7, respectively. Focusing on Table 6, the first column contains total impact of program participation on the farm household's welfare, decomposed into welfare contribution coming directly from adoption of new technology and indirectly from participation in the extension program. The second column contains total impact of inoculant adoption on the production frontier of inoculant adopters' relative to non-adopters, decomposed into the portion due directly to technological change which shifts the observed production frontier closer to the ideal production frontier (i.e., the potential yield frontier), and indirectly due to improvement in adopters' technical knowledge in shifting the production frontier. The estimates in the third column represent the total impact on the production efficiency of inoculant adopters relative to non-adopters, decomposed into efficiency gained due to technological change and indirectly due to improvement on inoculant adopters' technical knowledge.

The results in column one of Table 6 show that, the total treatment effect [measured as the local average treatment effect (LATE)] on yields is positive and statistically significant at the 1% level. Specifically, the impact on yield is 34 kg/ha (and 47 GHC/ha for net returns), suggesting that farmers who

TABLE 6 Productivity, efficiency and welfare estimates on soybean yield—(lnKg/ha).

Impact on: welfare	Technology frontier	Inefficiency frontier
LATE	**$LATE_h$**	**$LATE_g$**
34.423*** (0.820)	−134.670*** (3.236)	−168.969*** (3.862)
DLATE	**$DLATE_h$**	**$DLATE_g$**
12.292*** (0.739)	−46.027*** (2.861)	−58.360*** (3.554)
ILATE	**$ILATE_h$**	**$ILATE_g$**
22.140*** (0.516)	−88.610*** (1.993)	−110.685*** (2.480)

***1% level of significance; Values in brackets are bootstrapped standard errors from 1,000 re-samples. LATE is local average treatment effect, representing the total effect of participation in the extension dissemination program and inoculant adoption; DLATE is direct local average treatment effect, representing the component of the total effect that comes from inoculant adoption; ILATE is indirect local average treatment effect, representing the component of the total effect that comes from extension participation. The welfare measure represents the net effects of the potential outcomes of the shift in the technology and the inefficiency frontiers computed at the means.

TABLE 7 Productivity, efficiency and welfare estimates on net returns—(lnGHC/ha).

Impact on: welfare	Technology frontier	Inefficiency frontier
LATE	**$LATE_h$**	**$LATE_g$**
47.109*** (0.568)	−185.790*** (2.269)	−232.824*** (2.653)
DLATE	**$DLATE_h$**	**$DLATE_g$**
35.037*** (0.525)	−118.119*** (1.891)	−153.188*** (2.341)
ILATE	**$ILATE_h$**	**$ILATE_g$**
12.066*** (0.300)	−67.663*** (1.531)	−79.684*** (1.785)

***1% level of significance; Values in brackets are bootstrapped standard errors from 1,000 re-samples. LATE is local average treatment effect, representing the total effect of participation in the extension dissemination program and inoculant adoption; DLATE is direct local average treatment effect, representing the component of the total effect that comes from inoculant adoption; ILATE is indirect local average treatment effect, representing the component of the total effect that comes from extension participation. The welfare measure represents the net effects of the potential outcomes of the shift in the technology and the inefficiency frontiers computed at the means.

participate in the extension program and adopt the inoculant technology increased their yields (and net returns), compared to if they had neither participated in the extension program nor adopted the inoculant technology. A decomposition of the welfare benefits due to mediation indicate that 36% (i.e., DLATE = 12 kg/ha) of the welfare benefits, in terms of marginal gains in yield, can be attributed to the farm household's adoption of improved technology (i.e., the inoculant), while 64% (ILATE = 22 kg/ha) is due to the farm household's participation in inoculant extension dissemination program.

The total treatment effect on the production frontier in column two of Table 6 shows that, the technological change led to a reduction in the yield gap between the production frontier of adopters and that of the best production frontier by 135 kg/ha. In order words, farmers who participated in the extension program and adopted the inoculant technology increased their yields by 135 kg/ha, a finding that is similar to that of Ulzen et al. (2018) who found 200 kg/ha increased in soybean yields with inoculant application in northern Ghana. Further decomposition of the impact on the shift of the production frontier shows that 34% (i.e., $DLATE_h = 46$ kg/ha) is due to adoption of the improved technology, while 66% ($ILATE_h = 89$ kg/ha) of the shift is due to enhancement in farmers' technical knowledge on the improved technology usage. Intuitively, the total effect is an interaction of adoption of the improved technology and technical knowledge in the management of the new technology that leads to realization of the full potential of the technology (Takahashi et al., 2020).

In column three of Table 6, the total effect on the technical efficiency shows that improvement in technical efficiency of farmers led to an increase in yield of about 169 kg/ha. This indicates that farmers who participate in the extension program and adopt the inoculant technology are able to cut down their inefficiency up to 169 kg/ha (i.e., yield that would have been lost due to inefficiency) by adopting improved technology with technical knowledge. The marginal gain due to technical efficiency appears to slightly outweigh that of yield at the production frontier (i.e., 135 kg/ha). This finding is consistent with the argument by Huang and Liu (1994) that farmers who acquire technical knowledge on a new technology prior to adoption of the technology tend to benefit more. A decomposition of the total effect of technical efficiency shows that 34% (i.e., $DLATE_g = 58$ kg/ha) of the improvement comes from the farmer's adoption of improved technology, while 66% ($ILATE_g = 110$ kg/ha) comes from technical knowledge on the technology, implying that the synergic effect of better technology and technical knowledge is required for farmers to be fully technically efficient. However, greater proportion of the improvement in productivity is achieved through the extension participation sub-component (i.e., *ILATE*), compared to the improved technology adoption sub-component (*DLATE*), implying that providing farmers with superior technology without knowledge on its usage could result in underexploiting the full potential of the technology. We find similar patterns of impact on the production technology frontier and the technical efficiency frontier in the net returns model presented in Table 7.

Production and technology gap profiles

In Figures 2, 3, we present the conditional (i.e., condition on being a complier) mean yield estimates in deciles across various sub-populations of adopters at the production technology and technical inefficiency frontiers, respectively (see Figures A2, A3 in the Supplementary material for net returns). This is important in characterizing the production and technology gap between the various sub-populations of adopters and non-adopters, since adoption of an improved technology may induce inequalities in the production structures of farmers, due to heterogeneity in production technology and technical efficiency of farmers at the respective frontiers. Recent literature in the stochastic frontier

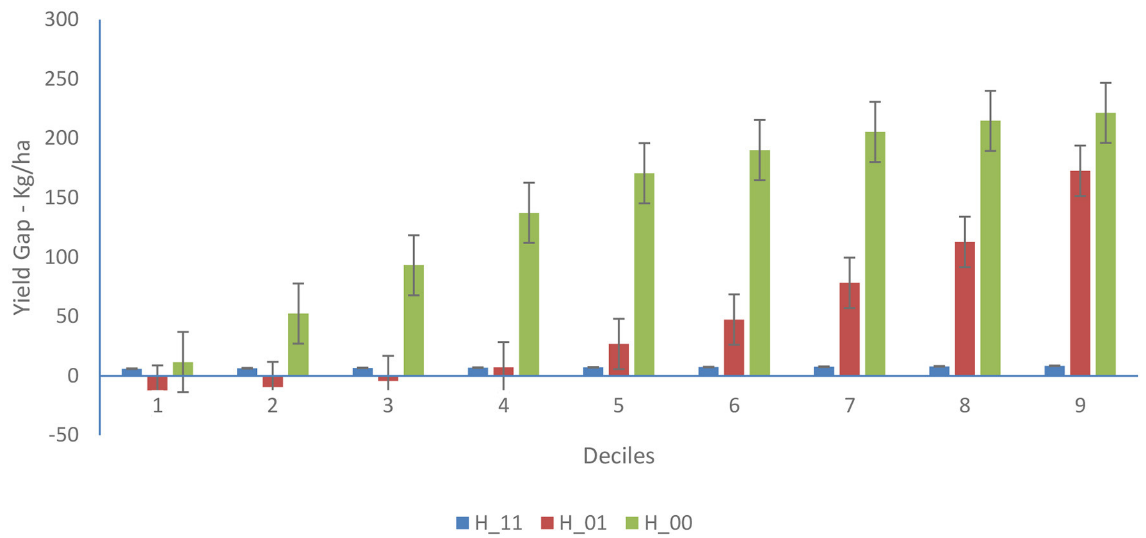

FIGURE 2
Yield gap profile at the production technology frontier (Kg/Ha). Where H-11, H-00 and H-01 indicates mediated-adopters, non-mediated-non-adopters and mediated-non-adopters, respectively at the production technology frontier function of yield. The figure illustrates the yield gap profile in deciles of farmers operating at different production technology frontiers, compared to farmers at the best production frontier operating at zero technological inefficiency.

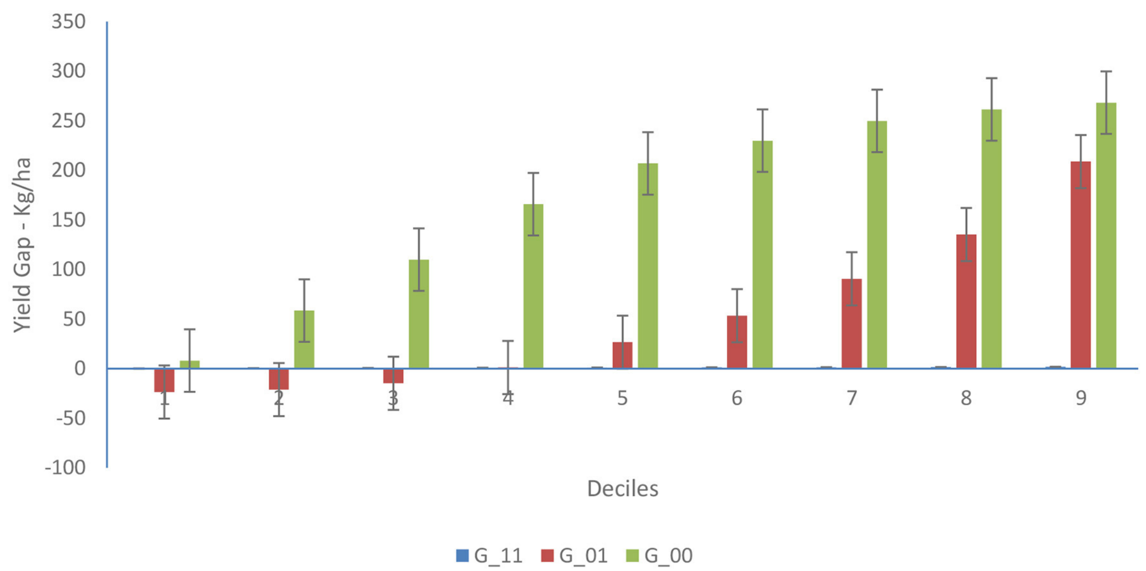

FIGURE 3
Yield gap profile at the inefficiency frontier (Kg/Ha). Where G-11, G-00 and G-01 indicates mediated-adopters, non-mediated-non-adopters and mediated-non-adopters, respectively at the technical inefficiency function of yield. The figure illustrates the yield gap profile in deciles of farmers operating at different levels of technical inefficiency, compared to farmers operating at zero technical inefficiency.

analysis employs quantile regression to profile the production and technology gap among firms for structural analysis (e.g., Huang et al., 2017; Lai et al., 2020). However, the quantile regression approach is somehow restrictive as it allows for characterization of firms only at the quantile means and not at the individual firm level means, as in the case of standard regression (Fortin et al., 2011), the approach employed in this paper.

Figure 2 shows that, the yield distance of farmers who participate in the extension program and adopt the inoculant technology [i.e., the MA farmers (H-11)] at every decile is closer to zero, compared to farmers who neither participate

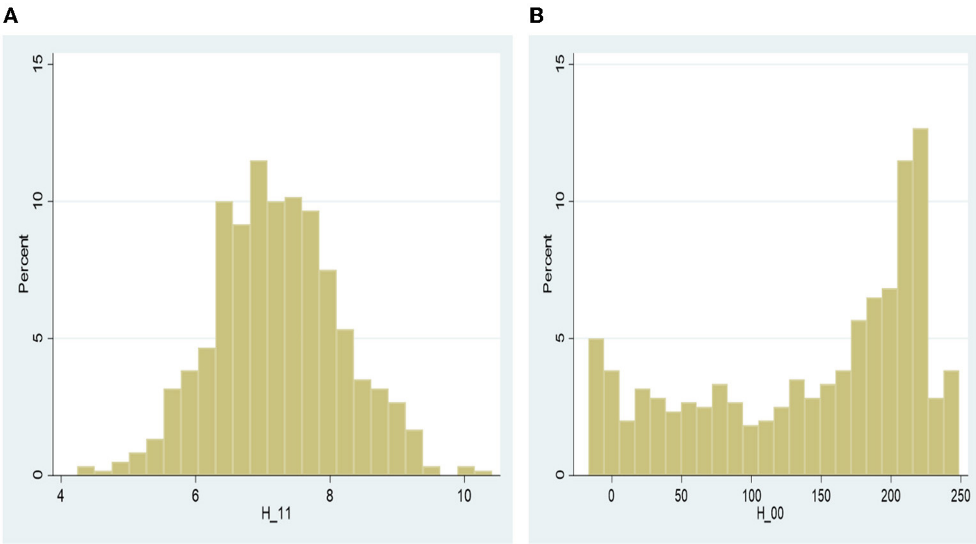

FIGURE 4
Comparison of yield (Kg/Ha) distributions at the technology frontier—direct effect. **(A)** Mediated-adopters, **(B)** non-mediated-non-adopters.

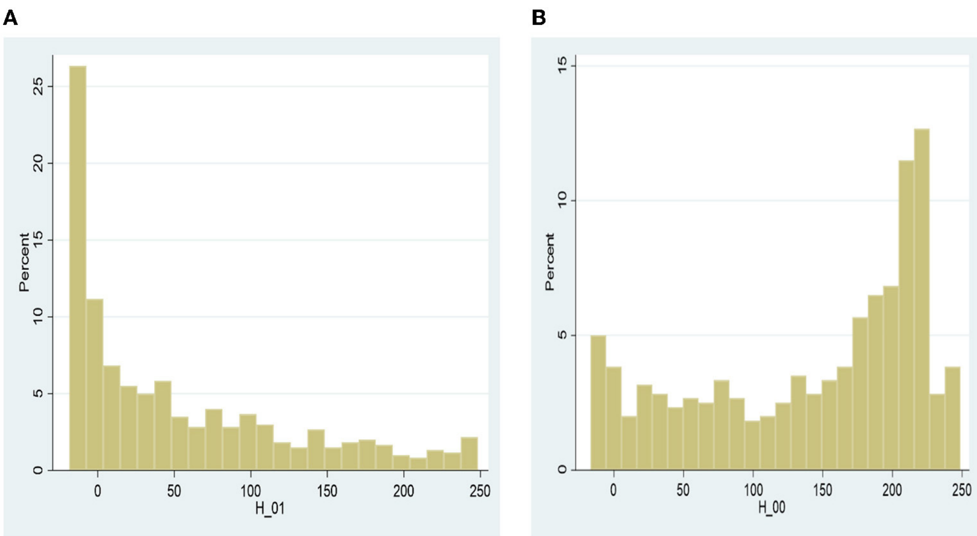

FIGURE 5
Comparison of yield (Kg/Ha) distributions at the technology frontier—indirect effect. **(A)** Mediated-non-adopters, **(B)** non-mediated-non-adopters.

in the extension program nor adopt the technology [i.e., the NM-NA farmers (H-00)]. Similarly, the MA farmers' yield gap is also narrower at the upper deciles (i.e., >4th decile), compared to farmers who participate in the extension program, but did not adopt the inoculant [i.e., the M-NA farmers (H-01)]. This implies that farmers who participated in the extension program before adopting the inoculant technology are closer to farmers producing at the best production frontier relative to other category of farmers. A similar pattern of distribution in the yield gap is observed in Figure 3, the conditional mean plot of the yield at the technical efficiency frontier. Figure 3 shows that, the average yield distance of MA farmers (G-11) at every decile is almost on the zero line, as compared to that of NM-NA (G-00) and M-NA (G-01) farmers respectively, indicating that farmers who participate in the extension dissemination program and adopt the inoculant are

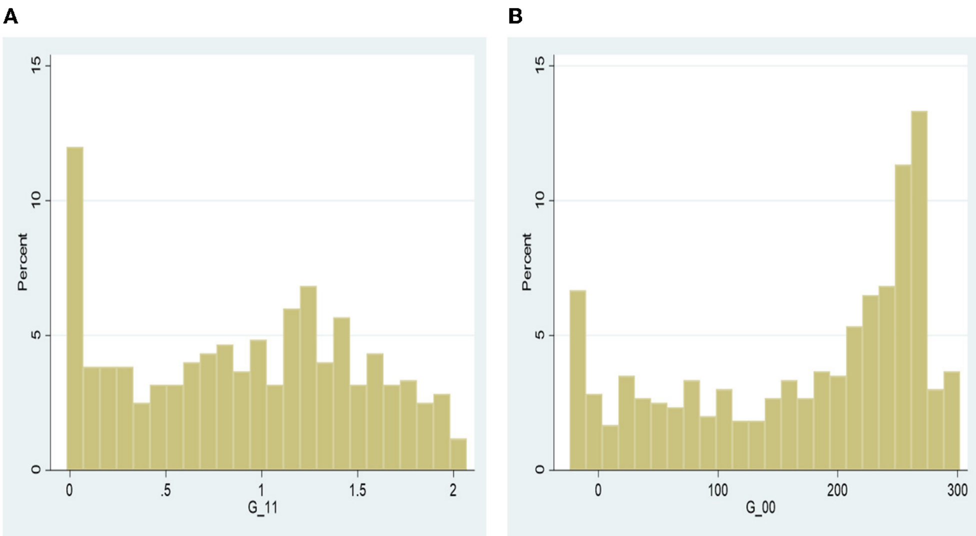

FIGURE 6
Comparison of yield (Kg/Ha) distributions at the inefficiency frontier—direct effect. **(A)** Mediated-adopters, **(B)** no-mediated-non-adopters.

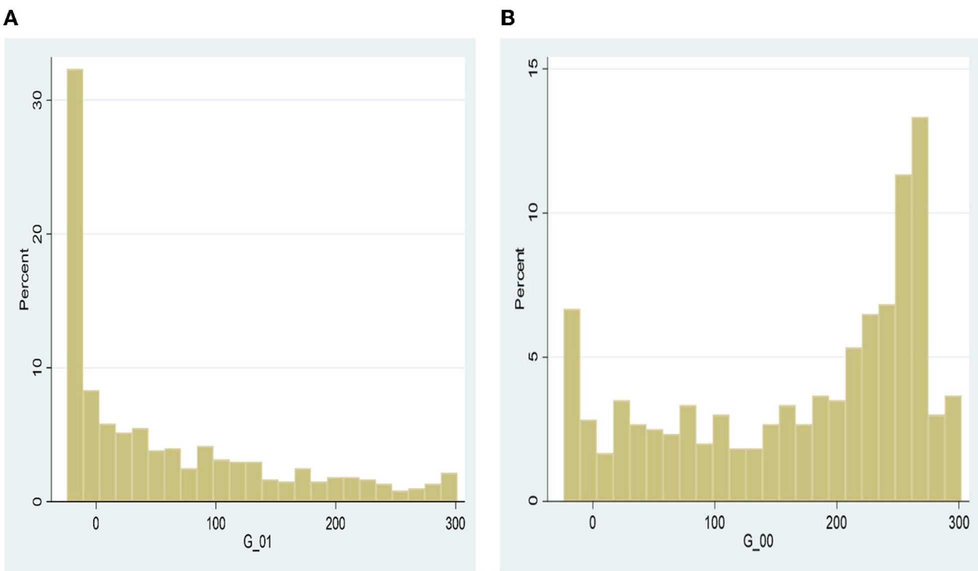

FIGURE 7
Comparison of yield (Kg/Ha) distributions at the inefficiency frontier—indirect effect. **(A)** mediated-non-adopters, **(B)** no-mediated-non-adopters.

technically more efficient than those who neither adopt nor participate in the dissemination program.

However, a comparison of the yield distance at both the production frontier and the technical efficiency frontier between farmers who participated in the extension dissemination program but did not adopt the inoculant [i.e., the M-NA farmers—(H-01 and G-01)] is also lower, when compared to that of NM-NA farmers (i.e., H-00 and G-00), suggesting that extension participation even without adoption of a new technology may still be effective in improving farmers' productivity, compared to zero extension provision. We find similar production and technical efficiency profile patterns in the net returns estimates presented in Figures A2, A3 in Supplementary material.

Figures 4, 5 show the full conditional mean yield gap distributions for MA farmers (H-11) in Figure 4A, compared to NM-NA farmers (H-00) in Figure 4B and also that of M-NA (H-01) farmers in Figure 5A, compared to NM-NA (H-00) farmers in Figure 5B, respectively. The mean yield gap distribution at the production technology frontier of MA farmers is much lower (within 10 kg/ha), compared to that of the distributions of NM-NA and M-NA farmers. This observation implies that greater percentage of the yield variability among the farmers may be attributed to technology heterogeneity, which significantly minimizes the yield distance between the farmers' production frontier and that of farmers at the best production frontier. Similar pattern of distribution is observed for the net returns in Figures A4, A5 in the Supplementary material.

Similarly, the mean yield gap distribution at the technical efficiency frontier in Figures 6, 7 show that the distribution for MA farmers (i.e., G-11) is densely skewed to the left (i.e., toward zero—within 2 kg/ha), compared to that of NM-NA (i.e., G-00) and M-NA (G-01) farmers, respectively. This results indicates that conditional on participating in the extension dissemination program and adopting the inoculant technology, all else being equal, greater percentage of yield variability at the frontiers may be due to random noise rather than technical inefficiency. We observed similar distribution patterns for the net returns in Figures A6, A7 in the Supplementary material.

Policy implications and conclusions

Our findings revealed that investing in either development of improved agricultural technologies such as the inoculant or intensifying extension delivery programs can to lead to increased productivity, as well as efficiency and welfare gains. Specifically, the study found that the contribution of adoption of improved agricultural technology alone (i.e., inoculant adoption) can lead to direct improvement in farm productivity, or indirectly through improved farmer efficiency led productivity gains, resulting in overall household welfare gains.

The study also made similar findings on extension delivery program participation alone, whose impact however, outweighs that of improved technology adoption alone. Our findings further indicate that making improved agricultural technologies available to farmers without complimentary extension knowledge supply could result in under exploiting the full potential of the technology. As the synergic effects of the two appears to be far greater than their individual effects.

The findings also show that investment in research and development to produce yield enhancing agricultural technologies suitable for poor and degraded soil conditions for farmers in developing countries, such as Ghana, can contribute immensely to poverty and food insecurity reduction. The development of new agricultural technologies must be pursued with vigorous provision of extension services to farmers, given that extension agents provide farmers with necessary knowledge needed to exploit the full potential of the technologies.

Our findings also reveal the significance of rural electrification in enhancing the diffusion and adoption of new agricultural technologies. Specifically, new agricultural technologies that need cold storage such as the *rhizobia* inoculant technology could go a long way to increase farm incomes and reduce rural poverty. This will also facilitate the deployment of new communication channels, such as the information and communication technologies (ICT) channels that rely on electricity for effective functioning, for extension delivery. As argued in this study, investment in rural electrification will also drive the development and expansion in rural enterprises such as sales of agro-inputs and perishable agro-based products, which must be stored under specific storage conditions.

Finally, our findings reveal that a policy intervention that subsidizes the inoculant technology to female farmers, who often have less access to extension services and quality land, will greatly improve their productivity.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation. The codes can be found under the Supplementary material at the publisher's web site https://doi.org/10.1080/07350015.2018.1497504.

Author contributions

The study's conception and design was done by SM and AA. Material preparation, data collection, analysis, and the first draft of the manuscript was written by SM. Edited and reviewed by AA. Both authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fsufs.2022.1025225/full#supplementary-material

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An economic assessment of adoption of hybrid rice: Micro-level evidence from southern China

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The hybrid rice technology could be considered a boon for food security for many in South and Southeast Asia to increase rice productivity. In China, the birthplace of hybrid rice (HR), the diffusion of hybrid rice started in 1976. About 28% rice-growing area in China is planted with hybrid rice. However, the proportion of HR area in China has been declining in recent years, and farmers in surrounding countries are reluctant to adopt it because of high seed costs, farm management practices, and quality issues. Most previous research on the evaluation of hybrid rice variety on yield does not control input level. This study uses the endogenous switching regression method to analyze the impacts of HR adoption on rice yield and net rice income. The study uses plot- and household-level data from four southern provinces of China. Findings show a significant effect of HR adoption on rice yields. On the same HR plots, compared to CR adopters, rice yield increases by 4.86% for HR adopters. Rice yield would increase by 4.72% if the HR variety was adopted on the same conventional rice (CR) plots. Additionally, findings show a significant effect of HR adoption on net rice incomes. On the same HR plots, compared to CR adopters, net rice income decreases by 43.61% for HR adopters. Similarly, net rice income would reduce by 10.95% if the HR variety was adopted on the same CR plots. Thus, adopting HR increases rice productivity, but Chinese farming households that adopted CR would not benefit from adopting HR. Policymakers can formulate a systematic and comprehensive rice breeding plan to guide the simultaneous development of rice variety yield and quality improvement. Additionally, policymakers, in conjunction with private companies, could enact policies to reduce the cost of hybrid rice seed or improve the production efficiency of HR. For example, they could incentivize the development of HR varieties suitable for direct seeding and seed-saving sowing methods (rice trans-planter).

KEYWORDS

fertilizer, seeds, farming households, rice seasons, pesticides, yields, income

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Introduction

The Green Revolution that began in the 1960s solved a widening Asian food crisis in the 1960s and lifted tons of people out of poverty (Evenson and Gollin, 2003; Hazell, 2009).[1] China is the largest rice-producing and rice-consuming country in the world. Indeed, rice accounts for 30 percent of the total grain acreage in China and 34% of grain output in 2019. China's rice crop supplies 28% of the global rice supply (FAOSTAT, 2015). Li et al. (2009) argue that the Chinese rice sector still faces surpluses or deficits in rice production. As a result, Chinese consumers are directly affected by increased variability in rice prices. China still faces population pressures and a land-population crisis. China wants to increase agricultural output for food security and the livelihood of millions of Chinese. To this end, China has used hybrid rice technology to increase rice yield per unit. Li et al. (2009) note that rice yields increased by 44% due to hybrid rice varieties, and rice acreage decreased by 14% between 1978 and 2008. Indeed, increased rice output has helped feed 60 million more Chinese annually.

Figure 1 shows the total rice-growing area planted with hybrid rice (solid line) and conventional rice (dash line) from 1983 to 2019. On the one hand, the figure reveals that the area planted with hybrid rice grew rapidly until the early 1990s. Since then hybrid rice area appears to flatten out with fluctuations until 2008. Strikingly, after 2008 the area under hybrid rice has been steadily declining. On the other hand, Figure 1 shows that area planted with conventional rice (CR) first decreased and then rebounded steadily since 2003. One can also observe that the planting gap between HR and CR was minimal in 2019. Not surprisingly, the above national pattern holds for the four provinces from which we collected our data (see Figure 2). Indeed, Table 1 shows that the yield from the hybrid rice variety is higher than the average yield of conventional rice of the four provinces in our study.

Despite their contributions over time and space, some studies show that the hybrid rice varieties are not attractive to farmers in several Asian countries (Janaiah et al., 2002; Spielman et al., 2017; Digal and Placencia, 2020). In addition, recent years have witnessed a decrease in the adoption of hybrid rice varieties in China (see Figures 1, 2). Although hybrid rice has a yield advantage, it also has higher input costs and lower market prices. In addition, with an improved breeding method, conventional rice can achieve high yields today. As a result, hybrid rice may not outperform conventional rice from the perspective of economic performance. Thus, rice farmers prefer conventional rice varieties when considering the difference in price, yields, and inputs.

FIGURE 1
Cultivation Area of HR and CR in China from 1983 to 2019 (unit: 10,000 ha). Source: Statistical Table of the Popularization of Main Crop Varieties in China, obtained from the China Agricultural Technology Extension Service Center. Notes: The data only includes rice varieties with a cultivation area larger than 100,000 mu (15 mu = 1 ha).

Therefore, the objective of this study is to provide an economic assessment of hybrid rice vs. conventional rice using plot-level repeated cross-sectional data collected from four major rice-growing provinces in southern China. Specifically, the study examines the impact of HR and CR on rice yields and net income earned from rice cultivation. We confirm hybrid rice has higher yields and input costs than conventional rice. We do not find strong evidence that hybrid rice would generate a higher net income for rice farmers in China. Our results have implications regarding the future direction of seed breeding. Policymakers should invest in breeding hybrid rice varieties to produce better grain quality at a lower cost. In addition, breeding methods of conventional modern rice varieties should also be encouraged.

Background and literature review

Using a three-line system, Chinese rice breeders started the hybrid rice program in 1964. In 1975 the hybrid rice (HR) technology became commercialized, and large-scale production of HR began in China. HR technology started to diffuse in China in 1976.[2] About 28% of China's rice-growing area was planted with hybrid rice by 1986 (Lin, 1991). The main advantage of hybrid rice is its high yield. In 1981, researchers in China bred a hybrid rice seed variety that yielded more than 500 kg/mu[3] (Xie et al., 1987; Ren et al., 2016; Wu et al., 2018). For example, Lin (1994) found that the yield advantage of hybrid rice over conventional rice is about 19% in China. Interestingly,

1 Evenson and Gollin (2003) show that high-yielding varieties increased rice productivity by about 0.8% per annum.

2 Other countries like the Philippines, India, Bangladesh, and Vietnam import hybrid rice seeds from China (Food and Agriculture Organization, 2014).

3 1 mu = 1/15 hectare.

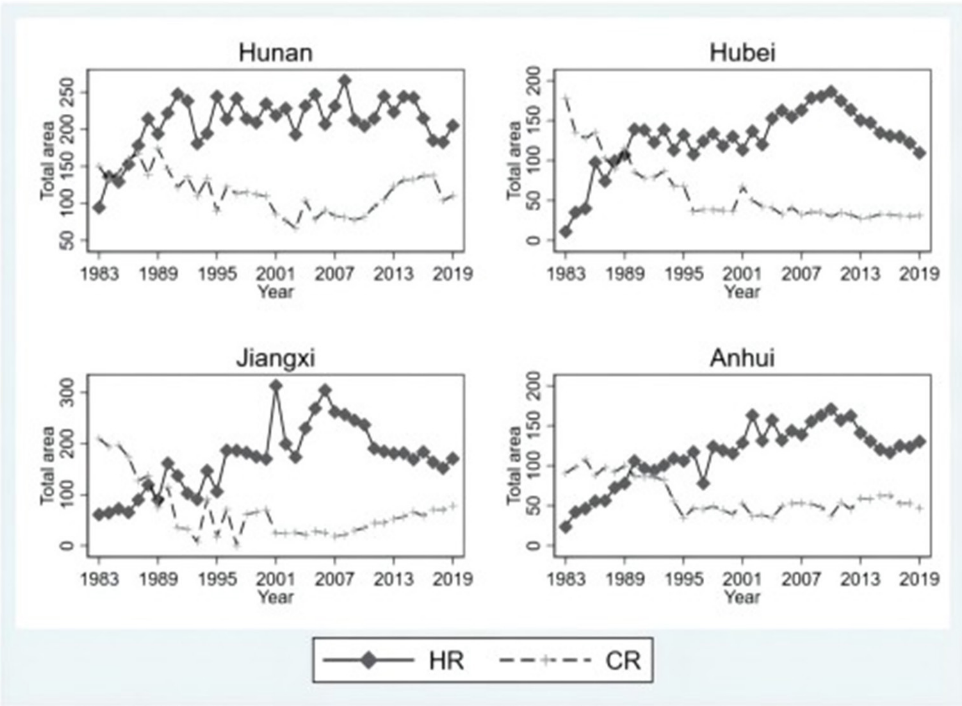

FIGURE 2
Cultivation Area of HR and CR from 1983 to 2019 by Surveyed Provinces (unit: 10,000 ha). Source: Statistical Table of the Popularization of Main Crop Varieties in China, obtained from the China Agricultural Technology Extension Service Center. Notes: The data only includes rice varieties with a cultivation area larger than 100,000 mu (15 mu = 1 ha).

more than a decade later, Zhao (2008) found that the yield advantage of hybrid rice over conventional rice was reduced to 12%. In other large rice-consuming Asian countries, the yield advantage of hybrid rice gain is about 15–20% higher than the high-yielding modern varieties (Janaiah et al., 2002; Mottaleb et al., 2015). In contrast, a recent study by Chau and Scrimgeour (2022) of Vietnamese rice farmers found that hybrid rice provided no yield superiority over high-yielding inbred rice. The authors tend to corroborate Lu et al.'s (2020) findings that inbred lines have higher yields than hybrid rice under higher planting density and reduced nitrogen application rate.

In terms of input demand, however, it is not clear that hybrid rice is less costly, and the findings in the literature seem mixed. Although hybrid rice uses less labor input and draft animal services, it demands more chemical fertilizer (Lin, 1994). Other studies show that hybrid rice uses less fertilizer (Li et al., 2014; Jammalamadaka and Deka, 2020). Finally, in recent research using experimental plot-level data, Lu et al. (2020) found that increasing planting density can reduce nitrogen application in rice production using inbred rice varieties. To that end, increasing planting density required a higher seeding rate in rice production. In other words, rice farmers have to use more seeds. Commercial companies in China produce hybrid rice seeds. Indeed, private companies are engaged in rice seed production across many countries in Asia, including India, Nepal, and Indonesia (Mishra et al., 2016). However, the price of hybrid rice seed is much higher than that of conventional rice seed (about ten times higher in our sample, see Table 1). Chau and Scrimgeour (2022) report that hybrid rice seeds cost twice as much as inbred seed varieties. Finally, labor and land preparation costs are two major rice production costs affecting rice farmers' bottom line. In recent years, Chinese rice farmers have adopted the direct-seeded rice (DSR) establishment method that uses less labor and reduces land preparation costs. However, Mishra et al. (2017) and Sha et al. (2019) noted that the DSR establishment method requires more seed quantity. Given the higher hybrid seed prices and the DSR method requiring more seed quantity, it is optimal for farm households to switch to conventional rice with lower seed costs. Most previous studies on the impact of hybrid variety on rice yields did not control for the input differences, which may exaggerate the effects of varietal differences.

The rice breeding method of conventional rice has undergone significant changes in recent years. As a result, the yield potential of conventional rice has increased significantly. Studies by Yang et al. (2004) and Zhang et al. (2015) argue that some conventional rice seed varieties can reach a similar or even higher yield level as hybrid rice seed varieties. In contrast,

TABLE 1 Variables and summary statistics, China.

Variable	HR (N = 845, 69%)		CR (N = 385, 31%)		*t*-statistics
	Mean	SD	Mean	SD	
Panel A. Household level					
Age of household head (years)	57.89	10.15	59.36	9.27	−1.466*
Education of household head (years)	6.24	3.18	5.99	2.98	0.26
Household labor size	3.15	1.52	2.81	1.51	0.340***
Large machine owned (dummy)	0.27	0.44	0.31	0.46	−0.04
Non-agricultural income ratio (%)	64.11	38.38	57.33	36.18	6.780**
Panel B. Plot level					
Plot size (mu [a])	9.16	83.72	5.37	9.05	3.79
Labor input (man day/mu)	4.12	3.20	2.06	1.75	2.063***
Seed price (yuan/kg)	68.63	28.86	6.74	11.90	61.891***
Seed input (kg/mu)	1.73	2.60	7.79	4.48	−6.060***
Fertilizer price (yuan/kg)	8.92	3.88	8.58	3.57	0.34
Fertilizer cost (yuan/mu)	155.96	65.95	155.13	58.04	0.83
Pesticide cost (yuan/mu)	111.42	64.36	111.31	59.48	0.10
Machine-renting cost (yuan/mu)	208.74	109.65	173.22	73.22	35.523***
Seeding method (dummy)	0.40	0.49	0.90	0.30	−0.498***
Pesticide application method (dummy)	0.58	0.49	0.88	0.33	−0.300***
Harvesting method (dummy)	0.91	0.28	0.98	0.14	−0.067***
Soil quality (dummy)	0.33	0.47	0.39	0.49	−0.065*
Irrigation condition (dummy)	0.77	0.42	0.82	0.39	−0.05
Cold soaked plot (dummy)	0.18	0.38	0.18	0.39	−0.00
Rice season: early (dummy)	0.60	0.49	0.39	0.49	0.207***
Rice season: middle (dummy)	0.12	0.32	0.59	0.49	−0.471***
Rice season: later (dummy)	0.28	0.45	0.02	0.14	0.264***
Year (dummy)	0.54	0.50	0.68	0.47	−0.141***
Rice price (yuan/kg)	2.24	0.39	2.33	0.25	−0.097***
Panel C. Outcomes: Yield, net income					
Rice yield (kg/mu)	501.88	97.69	439.85	91.37	62.030***
Net rice income (yuan/mu)	277.28	469.36	417.86	302.83	−140.584***

Source: The data were compiled by the authors. The data collection was supported by the National Social Science Foundation of China (14BGL094), EU Project H2020 programme (No. 822730).
***, **, and * donate significant at the 1, 5, and 10% level, respectively.
[a] 1 mu = 1/15 hectare, 1 man day = 8 h. The average plot size is relatively larger because some farmers with larger land scale report the multiple plots as one plot.

the yield potential of hybrid rice has not improved compared to what it was two decades ago. Thus, the yield advantage of hybrid rice is not very appealing today. In addition, conventional rice has better quality and taste for human consumption (Yang et al., 2004; Fu et al., 2014), partially putting downward pressure on the market price of hybrid rice (Janaiah et al., 2002; Digal and Placencia, 2020). Specifically, we argue that small farmers who plant rice for home consumption pursue rice cultivation for quality and taste. Thus, they are more likely to plant or buy conventional rice. In the case of commercial or semi-commercial farms, farmers are more likely to consider income and production costs that are partly derived from the market price of rice and prevailing input prices. Furthermore, according to our survey data, we found that the market price of conventional rice is indeed higher than that of hybrid rice. The choice of conventional rice versus hybrid rice based on rice quality remains a question beyond this paper's scope.

The large-scale production and promotion of hybrid rice varieties, known as the Green Revolution, a breakthrough in crop science and technology in the 1960s, was a boon to the world for global food security (He et al., 2020; Mishra et al., 2022). However, the impact of the adoption of hybrid rice technology on the natural ecological environment cannot be ignored. We know that excessive use of fertilizers and pesticides that go along with hybrid rice negatively impacts the natural environment. Lin (1994) found that compared with

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conventional rice, the use of chemical fertilizer in hybrid rice increased by 6%. In addition, Fan (2020) believes that Green Revolution technologies, such as high-yield rice, have a negative impact on the natural ecological environment because of the use of large amounts of fertilizer and stresses on irrigation water resources, land degradation, and biodiversity damage. In a recent study, Mishra et al. (2022) concluded that new rice technologies should be developed with sustainable natural resource management, including water and land management. The authors note that sustainable production methods such as DSR can increase production even as land availability decreases and the frequency of water shortages increases.

Recently, some scholars argued that the economic advantage of hybrid rice has been disappearing in China (Fu et al., 2014; Liu et al., 2014). Combined with the above argument, it is unclear if hybrid rice would consistently outperform conventional rice economically. Scholars have documented that hybrid rice would be more profitable in China (Chen and Ma, 1984; Tao, 1987), the Philippines (Casiwan and Morooka, 2007) and India (Gogoi et al., 2020). We add to this literature by providing a quantitative assessment of the economic performance of hybrid rice versus conventional rice with micro-level data recently collected from four provinces in southern China. Our results shed light on the future directions of rice breeding programs, focusing on food policies for Asian countries, especially those with a large populations in China and India.

Data and descriptive analysis

In this section, we introduce our data and present descriptive statistics. We use 2-year repeated cross-sectional data containing detailed information on rice farmers in a major rice-growing area in Southern China. Since the middle and lower areas of the Yangtze River in China are the major rice-growing areas, we selected four provinces (Hunan, Hubei, Jiangxi and Anhui, see Figure 3). We selected Liling City and Nanxian in Hunan Province, Gong'an County, and Jianli County in Hubei Province; Xinjian County in Jiangxi Province; Tongcheng City in Anhui Province. Furthermore, we selected two villages in one town in each city (county) selected above. Finally, we randomly selected about 35 rice farmers from each village according to the name list of rice farmers supplied by the village committee. We collected detailed information on household characteristics for each household, including the age and education of the household head, family labor size, off-farm employment experience, and large agricultural machinery owned by the household. More importantly, we collected detailed plot-level data on rice seed variety adopted (HR vs. CR), farming patterns and system (e.g., seeding method, pesticide application method, harvesting method, irrigation method, and rice seasons), cost of rice production (e.g., seed price and input, hired labor, and pesticide and fertilizer costs), rice yield, prices, income from rice farming,

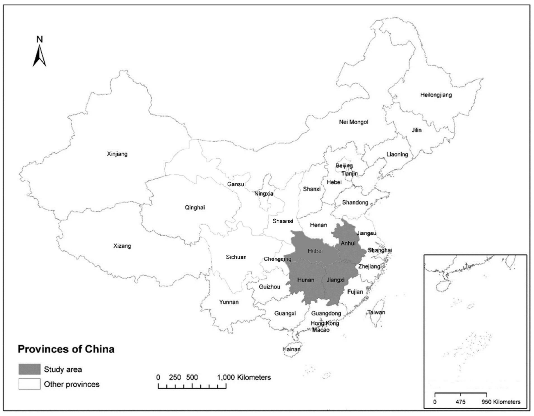

FIGURE 3
Location of surveyed Provinces. Source: Authors.

and land characteristics (e.g., size, soil quality, and cold-soaked degree). Given that we have plot-level information, we use the plot as the unit of analysis.

Table 1 presents the summary statistics and comparison of means of variables of interest between HR and CR plots (see Table A1 in Appendix for detailed variable definitions). In our sample, the farm households adopted HR (CR) seed variety for 69% (31%) of their land plots. Panel A of Table 1 presents the mean comparisons of household characteristics. The average age of household heads adopting HR seed variety is around 58, a year younger than their counterparts. There is no significant difference in household head years of schooling between farms HR and CR seed varieties, both of which approximately completed primary-school education (about 6 years of education). The mean household labor size of the families adopting the HR seed variety is significantly larger than their counterparts, even though the magnitude of the difference is not sizeable. Farm households adopting CR seed variety tend to be more likely to own large agricultural machinery (about 31%). In contrast, 27% of farmers adopting HR seed varieties own large machinery. Farm households adopting HR seed variety tend to earn more non-agricultural wage income than their counterparts.

Panel B of Table 1 reports the results of plot-level comparisons, focusing mainly on inputs of rice production. On average, the HR plot size is larger than the CR plot size, about 3.79 mu.[4] The above finding is consistent with the patterns observed in Figure 2. The seed price difference between the HR and CR plots is the most noticeable. The seed price of HR plots is about 69 yuan/kg, about ten times more than seed prices for CR plots. Although the seed input (1.7 kg/mu) is

4 Our sample includes 12 HR plots with size larger than 100 mu, therefore, the average size of HR plots is larger.

smaller for the HR plots than for the CR plots (7.8 kg/mu), the overall seed cost remains much higher than for the CR plots. For fertilizer and pesticide costs, the differences are not significant. Farm households with HR plots rent more machinery for cultivating and harvesting, indicating that farm families are less likely to own agricultural machines (see Panel A in Table 1).

The farm households use the DSR establishment method for 90% of the CR plots. However, only 40% of the HR plots use the DSR method. This is partly because the DSR establishment method requires more seed inputs (Sha et al., 2019). We do not observe a significant difference in plot quality between the HR and CR seed varieties. For instance, both plots have similar soil quality and cold-soaked levels. On average, Chinese rice farmers adopt the HR seed variety in the middle and later rice growing seasons. In contrast, Chinese farmers adopt the HR seed variety in the early and later rice-growing seasons. Lastly, we can see that the market price of CR is significantly higher than that of HR. Panel C of Table 1 compares the rice yield and income for HR and CR plots. The HR plots have higher yields, about 502 kg/mu, than the CR plots (440 kg/mu). Meanwhile, the CR plots have a higher net income from rice, about 418 yuan/mu, than the CR plots (277 yuan/mu).

Empirical framework

We use the endogenous switching regression (ESR) model to conduct our empirical analysis. We can view the farm households adopting hybrid rice (HR) seed variety and conventional rice (CR) seed variety as the treatment and control groups, respectively. Because the farm households may self-select into adopting HR seeds, the treatment (i.e., adopting HR seed variety) is endogenous, resulting in sample-selection bias (Heckman, 1979). The ESR model can account for this bias using a two-step estimation procedure. First, we model the adoption choices of farm households and estimate a selection equation. A farm household adopts HR seed variety based on the expected utility. Specifically, a Chinese rice farmer will adopt the HR seed variety if the expected utility from adopting the HR seed variety is greater than not adopting (or CR seed variety). In other words, the expected utility of adoption of HR seed variety, $U^{*}_{i,HR}$, is higher than the expected utility of CR seed variety, $U^{*}_{i,\,CR}$, where i denotes a plot. In the data, we can only observe whether a farm household adopts HR seed variety for a plot or not (indicated by U_i: an indicator variable) but fail to observe $U^{*}_{i,\,HR}$ and $U^{*}_{i,\,CR}$. Using this framework, we estimate a probit model as follows:

$$U_i = Z_i^{'}\alpha + \epsilon_{i,\,U} \; with \; U_i = \begin{cases} 1, & if \quad U^{*}_{i,\,HR} \geq U^{*}_{i,\,CR} \\ 0, & if \quad U^{*}_{i,\,HR} < U^{*}_{i,\,CR} \end{cases} \quad (1)$$

where Z_i is a vector of plot and household attributes, and α is a vector of parameters to be estimated. $\epsilon_{i,\,U}$ is the error term with a standard normal distribution.

Second, we then estimate the outcome equation based on the selection equation. We specify the following two regime equations (HR and CR plots) to explain the outcome variables:

$$\begin{aligned} Regime\ 1: \ Y_{i,\,HR} &= X_i^{'}\beta_{HR} + \epsilon_{i,\,HR} \\ Regime\ 2: \ Y_{i,\,CR} &= X_i^{'}\beta_{CR} + \epsilon_{i,\,CR} \end{aligned}, \quad (2)$$

where $Y_{i,\,HR}$ and $Y_{i,\,CR}$ are the outcomes of our interest (namely, yield and net rice income) if a farm household adopts HR and CR seed varieties for land plot i, respectively. Only one of $Y_{i,\,HR}$ and $Y_{i,\,CR}$ is observable for land plot i, so we need to construct the counterfactual outcome to estimate the treatment effects. X_i includes plot-level and household-level explanatory variables, which we allow to be overlapped with Z_i, following Fuglie and Bosch (1995). β_{HR} and β_{CR} are vectors of parameters to be estimated. Finally, $\epsilon_{i,\,HR}$ and $\epsilon_{i,\,CR}$ are error terms, both of which are assumed to have a normal distribution. All the three error terms ($\epsilon_{i,\,U}$, $\epsilon_{i,\,HR}$ and $\epsilon_{i,\,CR}$) have the following variance-covariance structure:

$$\begin{pmatrix} \epsilon_U \\ \epsilon_{HR} \\ \epsilon_{CR} \end{pmatrix} \sim \left(\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho_{U,\,HR}\sigma_{HR} & \rho_{U,\,CR}\sigma_{CR} \\ \rho_{U,\,HR}\sigma_{HR} & \sigma^2_{HR} & \rho_{HR,\,CR}\sigma_{HR}\sigma_{CR} \\ \rho_{U,\,CR}\sigma_{CR} & \rho_{HR,\,CR}\sigma_{HR}\sigma_{CR} & \sigma^2_{CR} \end{pmatrix} \right), \quad (3)$$

where $\rho' s$ are correlation coefficients and $\sigma' s$ are standard deviations. Finally, to estimate the treatment effects of adopting the HR seed variety, we construct the counterfactual outcome for plots when farm households adopt HR seed variety and plots when farm households adopt CR seed variety (Mishra et al., 2017). In total, we have the following four cases:

$$\begin{aligned} &\text{HR plots with adoption (observed)}: E\left(Y_{HR} \mid U = 1\right) \\ &= X^{'}\beta_{HR} + \rho_{U,\,HR}\sigma_{HR}\lambda_{\epsilon HR}; \quad (4) \\ &\text{HR plots without adoption (counterfactual)}: E\left(Y_{CR} \mid U = 1\right) \\ &= X^{'}\beta_{CR} + \rho_{U,CR}\sigma_{CR}\lambda_{\epsilon HR}; \quad (5) \\ &\text{CR plots without adoption (observed)}: E\left(Y_{CR} \mid U = 0\right) \\ &= X^{'}\beta_{CR} + \rho_{U,CR}\sigma_{CR}\lambda_{\epsilon CR}; \quad (6) \\ &\text{CR plots with adoption (counterfactual)}: E\left(Y_{HR} \mid U = 0\right) \\ &= X^{'}\beta_{HR} + \rho_{U,HR}\sigma_{HR}\lambda_{\epsilon CR}, \quad (7) \end{aligned}$$

where λ is the inverse Mills ratio. Based on the observed and constructed counterfactual outcomes, we now can estimate the treatment effects of adopting HR variety and not adopting HR seed variety as follows:

$$\text{average treatment effect on the treated (ATT)} : ATT = E(Y_{HR} \mid U = 1) - E(Y_{CR} \mid U = 1); \quad (8)$$

$$\text{average treatment effect on the untreated (ATU)} : ATU = E(Y_{CR} \mid U = 0) - E(Y_{HR} \mid U = 0). \quad (9)$$

For each of our outcomes (yield and net rice income), we can calculate *ATT* and *ATU*, respectively.

Results and discussion

The empirical model was estimated using STATA software. The ESR models were used to evaluate the factors affecting rice yields and incomes and assess the impact of HR adoption on yields and net rice income.

Impact on rice yields

Table 2 presents the estimated impact of the adoption of HR on rice yields. In our study, we could not reject the Cobb-Douglas specification of the production function.[5] Addtionally, the lower part of Table 2 reveals the coefficient of IMR was negative and statistically significant, and estimated covariance terms and statistics confirm heterogeneity, indicating that without the correction, estimates from the model would have resulted in biased estimates (downward-biased). In addition to the factors of production, we also control for variations in household attributes (education, age, experience, family size) and plot attributes in our selection and outcome function. Note that the selection and outcome equations are estimated jointly in the ESR procedure. Following Lokshin and Sajaia (2004), the selection equation should contain all instrumental and explanatory variables. To identify the model better, the selection equation should include all explanatory variables in the outcome equation plus at least one instrumental variable. The instrumental variable is related to the adoption of hybrid rice varieties but not to the outcome variables. In our case, we used the proportion of hybrid rice at the provincial level and rice season (early and later) as instruments in the selection function. The second column of Table 2 shows the parameter estimates of the selection function. Table 2, column 2 shows that the adoption of HR is positively affected by labor input, fertilizer, pesticide, and machinery rental costs. Additionally, rice farmers growing rice early (March to July) are less likely to adopt HR variety than mid-season rice (May to October). In contrast, farmers are more likely to adopt the HR variety to grow rice in the late season (June to Oct/November) than farmers choosing the mid-season rice (May to October) planting season.

The two outcome equations are shown in columns 3 and 4 of Table 2. We observe some notable differences between the coefficients in the HR and CR varieties. For instance, in the HR equation, the coefficient of total labor input is positive and statistically significant at the 5% significance level. The result indicates that a 1% increase in total labor input increases HR yields by about 0.04% (higher than CR yields). Although that HR adoption has been declining in recent years, this finding shows that labor productivity may increase with the adoption of HR technology. Higher fertilizer costs indicate higher fertilizer use in rice production—a 1% increase in fertilizer costs increases rice yield by 0.02%. Our finding is consistent with Chau and Scrimgeour (2022), who note that HR varieties are expected to be responsive to fertilizer. However, the result in column 4 (Table 2) shows that fertilizer's cost has a higher impact on CR yields. Specifically, a 1% increase in fertilizer costs increases rice CR rice yields by 0.09%. A similar trend is observed for pesticide and machine-renting costs of rice HR and CR yields. Hossain et al. (2006) noted that hybrid rice is sensitive to plant diseases and thus requires greater pesticide usage. For pesticide cost, Table 2 reveals that the magnitude of the coefficient is bigger in the case of HR technology compared to the magnitude obtained for CR technology. However, for machine-renting cost, the coefficient's magnitude is smaller in HR technology compared to the magnitude obtained for CR technology.

Table 3 presents the average treatment effects of HR adoption on rice yields—see Equations 8, 9. Table 3 reports the net impacts, controlling for adverse HR effects and other confounding factors. Findings in Table 3 show that HR rice farmers would have significant, albeit smaller, lower rice yields if they had not adopted HR—an ATT of about 4.86%. Finally, Table 3 reveals a positive and significant ATU, meaning that average rice yields on CR variety plots could be 4.72% higher if the HR variety were adopted on those plots. The large difference between ATT and ATU signal heterogeneity in impacts is due to agronomic, production, and socioeconomic attributes. Thus, we can say that heterogeneity makes the adopters of HR better rice producers than CR producers, irrespective of their adoption.

Impact on rice income

Table 4 shows the ESR estimates of the ESR model of net rice income at the plot level, differentiated by HR and CR plots. Based on model fitness parameters, the double-log specification showed the best fit. Specifically, the model has the logarithm of net rice income as the dependent variable and independent logarithm variables—rice prices, land, and inputs. Finally, the lower part of Table 4 confirms heterogeneity, and thus correction

5 Akaike Information Criterion (AIC) is used to describe the information loss of the constructed model relative to the "real model." The AIC value in the form of double logarithmic function is far lower than that in the form of linear function, indicating that the form of double logarithmic function has better fitting effect.

TABLE 2 ESR results for rice yield, China.

Variable	Selection function	Outcome function	
		HR	CR
Labor input (man day/mu [a], log)	0.514***	0.037**	0.022
	(0.190)	(0.017)	(0.034)
Seed input (kg/mu, log)	8.502***	−0.114	−1.973**
	(2.684)	(0.282)	(0.952)
Seed input-squared (kg/mu, log)	−4.406***	0.075	0.884**
	(1.193)	(0.129)	(0.424)
Fertilizer cost (yuan/mu, log)	0.176	0.023*	0.086***
	(0.117)	(0.013)	(0.024)
Pesticide cost (yuan/mu, log)	−0.055	0.044***	0.038**
	(0.105)	(0.011)	(0.017)
Machine-renting cost (yuan/mu, log)	0.052	0.028***	0.119***
	(0.102)	(0.008)	(0.023)
Seeding method (dummy)	−0.959***	0.036*	0.054
	(0.214)	(0.019)	(0.041)
Pesticide application method (dummy)	−0.261	0.005	−0.000
	(0.216)	(0.018)	(0.039)
Year (dummy)	−0.361	0.132***	0.144***
	(0.246)	(0.021)	(0.037)
Plot characteristic variables	Yes	Yes	Yes
Household characteristic variables	Yes	Yes	Yes
Proportion of hybrid rice at the provincial level	6.032***		
	(1.121)		
Rice season: early (dummy)	−1.464***		
	(0.254)		
Rice season: later (dummy)	0.177		
	(0.308)		
Intercept	−5.393***	5.452***	5.099***
	(1.654)	(0.151)	(0.401)
Sigma		−1.698***	−1.687***
		(0.032)	(0.051)
Rho		−0.747***	−0.505**
		(0.218)	(0.203)
Observations	812	812	812

The dependent variable for the outcome function is rice yield (kg/mu, log). Plot characteristics include soil, irrigation, and cold-soaked plot; household characteristics include the age of household head, education of household head, household labor size, large machinery owned, and non-farm income ratio.

[a] 1 mu = 1/15 hectare, 1 man day = 8 h.

***, **, and * donate significant at the 1, 5, and 10% level, respectively.

TABLE 3 Average treatment effects of HR on rice yield, China.

Plot	Obs.	HR		CR		Treatment effects	Ln%
		Mean	SD	Mean	SD		
HR plots	563	6.198	0.094	5.911	0.187	ATT: 0.287***	4.86
CR plots	249	6.351	0.074	6.065	0.114	ATU: 0.286***	4.72

*** donate significant at the 1% level of significance.

TABLE 4 ESR results for net rice income, China.

Variable	Selection function	Outcome function	
		HR	CR
Rice price (yuan/kg, log)	−3.032***	3.109***	1.617
	(0.998)	(0.861)	(2.090)
Seed price (yuan/kg, log)	1.168***	0.246	1.228
	(0.118)	(0.363)	(0.767)
Labor input (man day/mu [a], log)	0.333	−4.055***	−3.666***
	(0.379)	(0.382)	(0.565)
Fertilizer price (yuan/kg, log)	0.312	−1.586**	−0.927
	(0.498)	(0.638)	(0.901)
Plot size (mu, log)	0.319*	0.190	0.461
	(0.165)	(0.243)	(0.289)
Seeding method (dummy)	−0.716***	−0.204	0.503
	(0.245)	(0.356)	(0.584)
Pesticide application method (dummy)	−0.490**	0.434	−0.281
	(0.243)	(0.360)	(0.526)
Harvesting method (dummy)	−0.823	−0.875	0.059
	(0.570)	(0.598)	(1.348)
Year (dummy)	−0.155	−4.859***	−2.946***
	(0.433)	(0.649)	(0.881)
Plot characteristic variables	Yes	Yes	Yes
Household characteristic variables	Yes	Yes	Yes
Proportion of hybrid rice at the provincial level	2.431		
	(1.493)		
Rice season: early (dummy)	−0.756***		
	(0.270)		
Rice season: later (dummy)	0.586*		
	(0.320)		
Intercept	−1.999	10.804***	6.354*
	(2.093)	(2.590)	(3.698)
Sigma		1.256***	0.895***
		(0.030)	(0.072)
Rho		0.200	0.708
		(0.231)	(0.658)
Observations	812	812	812

The dependent variable for the outcome function is net rice income (yuan/mu, log). Plot characteristics include soil, irrigation, and cold-soaked plot; household characteristics include the age of household head, education of household head, household labor size, large machinery owned, and non-farm income ratio.

[a] 1 mu = 1/15 hectare, 1 man day = 8 h.

***, **, and * donate significant at the 1, 5, and 10% level, respectively.

TABLE 5 Average treatment effects of HR on net rice income, China.

Plot	Obs.	HR		CR		Treatment effects	Ln%
		Mean	SD	Mean	SD		
HR plots	563	3.932	2.555	6.975	2.201	ATT: −3.042***	−43.61
CR plots	249	4.686	2.050	5.262	1.754	ATU: −0.576***	−10.95

*** donate significant at the 1% level of significance.

is needed to derive unbiased parameter estimates. Column 2, Table 4 reveals that several factors, such as the price of rice, seeds, labor input, seeding method, and rice season, significantly affect the adoption of HR varieties. Indeed, the price received for their output has a significant negative effect on adopting the HR varieties. Our finding is consistent with the studies in the literature, Janaiah et al. (2002), Yang et al. (2004), Fu et al. (2014), and Digal and Placencia (2020), who argue that rice CR has better quality and taste and is preferred by consumers. Thus, negatively impacting the market price of hybrid rice.

Chinese rice farmers are less likely to adopt HR varieties if the rice establishment method is DSR than the puddled transplanted rice (PTR). Hybrid rice usually requires a PTR establishment method, and rice yields are low for HR using the DSR establishment method. Our finding is consistent with Yamano et al. (2013). The authors point out that cultivating HR in DSR plots is riskier than growing inbred or high-yielding varieties with the DSR method.

The outcome function estimates for HR and CR are reported in columns 3 and 4 of Table 4. The two columns show a noticeable difference in the significance and magnitude of the HR and CR plots. Rice price has the highest elasticity in both regimes. For instance, a 1% increase in rice price increases net rice income for HR output by 3.11%. Similarly, a 1% increase in rice price increases net rice income for CR output by 1.62%. The labor coefficient is negative and statistically significant at the 1% level of significance. Finding suggests that a 1% increase in labor man-days decreases the net rice income of the HR by ∼4.1%. The results are consistent with the agronomic requirements of HR production. HR tends to use more fertilizer and pesticides. Thus, fertilization and pesticide application require labor and greater use of labor in these two farming activities. Taken together, both higher amounts of rice seeds and labor inputs, components of variable costs, tend to increase total costs of production (Ma and Yuan, 2015) and result in lower net income from rice enterprises.

Table 5 shows the ATT of HR adoption on net rice income. The findings in Table 5 report the net impacts. In other words, the impact control for adverse HR effects and other confounding factors. Results in Table 5 show that farmers using HR technology on rice plots would have higher net rice income had they not adopted HR, a negative and significant ATT of about 43.61%. Additionally, Table 5 shows a negative and significant ATU, meaning net rice income from CR plots would be 10.95% lower if HR technology were used on CR plots. An explanation could be that Chinese farmers are using CR technology on plots that may be more suitable for CR technology because they know that if they plant hybrid rice on the same plot (the reality is to plant conventional rice), their net rice income will decline.

Conclusion and policy implication

The food security and livelihood of smallholders depend on the rice sector. Rice is a significant crop for most smallholders in Asia and Africa. China is the largest producer and consumer of rice in the world. The average rice yield in China is about 6 tons/hectare and is the highest in Asia. China is the largest adopter of hybrid rice. Hybrid rice variety has the potential to increase rice yields in the era of decreasing farm size. The present study analyzed the impact of hybrid rice in four provinces in southern China. The study used the ESR method, and we accounted for selection bias and heterogeneity impacts of the HR technology. A novel contribution of this study was that we account for heterogeneous effects on the adoption of HR technology. In addition to rice yields (productivity), a measure of food security, the study also analyzed HR adoption's net rice income effects.

After controlling for selection bias, the study found that adopting HR technology significantly increases rice yields by about 4.86%. However, the study found the opposite effect in the case of net rice income. The study found that adopters of HR technology decreased net rice income by 43.61%. Projections from this study showed that current non-adopters of HR technology (or CR farmers) would increase rice yields (4.72%) when they move to HR technology. Similarly, we discovered that non-adopter of HR (or CR farmers) reduced their net rice income (10.95%) when they switched to HR technology.

From a policy perspective, the analysis revealed that the quantity of seed and labor used in rice farming positively affects the adoption of HR technology. Thus, developing private seed markets and creating/encouraging competition by providing subsidies on HR seeds, seed dealerships, and accessibility to the input markets can support the proliferation of HR technology. The government can promote competition within private seed companies and provide farmers subsidies for buying HR seeds. For example, the Chinese government should conduct a routine and careful analysis of market conditions, including competition and concentration in seed companies, backed by effective enforcement of antitrust laws to ensure that seed markets remain competitive. This research has several implications for rice breeding programs at the national and international levels—CGIAR centers. First, rice breeding programs should consider improving the yield of rice variety while simultaneously paying attention to enhancing rice quality (Mottaleb et al., 2017).

Second, governments, in conjunction with private companies, could enact policies that reduce the cost of hybrid rice seed or improve the production efficiency of HR—for example, developing HR varieties suitable for direct seeding and seed-saving sowing methods (rice transplanter). The HR varieties may be advantageous in countries with low-yield conventional rice varieties. Recall that direct-seeded rice could potentially save about two labor days (nearly cost

200–300 yuan) input per mu for rice farmers in China. We need to point out that there is also a great improvement in the yield of conventional rice varieties in China in the past 30 years, which narrowed the yield gap between the HR and conventional rice varieties.

Finally, the study has limitations. First, the study relies on repeated cross-sectional data. Thus, due to the lack of panel data, the study could not assess the impact of HR technology over time. Second, this study only considers two broad rice categories: conventional and hybrid. Considering detailed sub-categories may also be necessary. Third, we could not correctly measure their contribution to the observed heterogeneity in rice yields due to the lack of data on quality differentials in seed and labor. Future studies could determine the effects of social networks, community organizations, and extension services. Finally, future research could also address environmental and resource outcomes and benefits to society.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

ZY: data cleaning, software, data analysis, and writing—original draft. FC: conceptualization, methodology, funding, resources, and writing—review and editing. AM: conceptualization, methodology, supervision, investigation, writing—original draft, and writing—review and editing. WS: data analysis, software, methodology, and writing—original draft. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Appendix

TABLE A1 Variable description.

Variable	Description
Panel A. Household level	
Age of household head (years)	Household head's age
Education of household head (years)	Years of schooling
Household labor size	Number of household labor
Large machine owned (dummy)	=1, if owning large machine; 0, otherwise
Non-agricultural income ratio (%)	Share of non-agricultural income in total income
Panel B. Plot level	
Labor input (man-day/mu[a])	Amount of labor used
Seed input (kg/mu)	Amount of seed used
Pesticide cost (yuan/mu)	Pesticide cost
Fertilizer cost (yuan/mu)	Fertilizer cost
Machine-renting cost (yuan/mu)	Total cost per mu of renting agricultural machine
Plot size (mu)	Area of cultivated plot
Seeding method (dummy)	=1, if adopts direct-seed rice; 0 otherwise
Pesticide application method (dummy)	=1, if by machine; 0, if by man
Harvesting method (dummy)	=1, if by machine; 0, if by man
Soil quality (dummy)	=1, if good soil quality; 0, otherwise
Irrigation condition (dummy)	=1, if good irrigation condition; 0, otherwise
Cold soaked plot (dummy)	=1, if cold-soaked plot; 0, otherwise
Year (dummy)	=1, if 2019; 0, if 2015
Seed price (yuan/kg)	Seed price
Fertilizer price (yuan/kg)	Fertilizer price
Rice price (yuan/kg)	Rice price
Rice season: early (dummy)	March to July
Rice season: middle (dummy)	May to October
Rice season: later (dummy)	June to October/November
Panel C. Outcomes: Yield, Net Income	
Rice yield (kg/mu)	Total rice yield per mu
Net rice income (yuan/mu)	Total net rice income per mu

Source: The data were compiled by the authors. The data collection was supported by the National Social Science Foundation of China (14BGL094), EU Project H2020 programme (No. 822730). [a] 1 mu = 1/15 hectare; 1 man day = 8 h.

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Improving women's purchasing power through land-enhancing technologies: The case of bio-reclamation of degraded lands in Niger

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In Niger, about 50% of the land surface is composed of degraded lateritic soils, and rural women farmers have limited access to productive land. Targeting largely marginalized rural women with bio-reclamation of degraded land (BDL) technologies restores their rights to earn a livelihood through agriculture. This study examines the determinants and impacts of land-enhancing technology on women farmers in Niger. Data were collected from 1,205 randomly selected women farmers in the Maradi and Zinder regions. The sample included 69% of participants into BDL program and 31% of non-participants. To account for selection bias from observable and unobservable factors, an endogenous switching regression (ESR) model was used to estimate the impact of BDL technology on women's household income. A simple probit model was used to analyze the determinants of participation. The results show that key determinants of participation in BDL include income level before participation in BDL, household size, age of participants, number of women in the household, number of children under 5 years old, sex of household head, age of household head, and institutional support. Participation in BDL positively influences participants' income (+14%); non-participants may not benefit from participating as they would probably lose 31% of their income, and the impact of participation in BDL varies widely across regions. Before the advent of BDL, the income of non-participants was higher than that of participants by 25%. It can be inferred that BDL is a pro-poor technology that is not beneficial to all women farmers. This study makes a critical contribution to the literature on land-enhancing technologies. It suggests that the impact of land-enhancing technologies, such as BDL, is closely linked to spatial, economic, environmental, temporal, and cultural contexts. Accordingly, land-enhancing technologies should target locations with large percentages of degraded farmlands and the poorest farmers. These results contribute to food security and poverty alleviation policies in rural dryland areas.

KEYWORDS

bio-reclamation of degraded lands, impact assessment (IA), welfare, endogenous switching regression model (ESRM), Niger

1. Introduction

Land degradation is a persistent deterioration of land productivity (Adeel et al., 2005). It is characterized by three types of soil degradation, namely, chemical, physical, and erosional (Orchard et al., 2017). It has been a major global issue since the 20th century (Hamdy and Aly, 2014), affecting an estimated 1.5 billion people and a quarter of the land area in all agroecological zones worldwide (Lal et al., 2012, 2014). Annually, an area of ∼5–8 million hectares of formerly productive land goes out of cultivation globally due to degradation (TerrAfrica, 2006). The African continent is particularly vulnerable to land degradation (Obalum et al., 2012; Reed and Stringer, 2016). More than 75% of arable land in the continent is degraded (Khan et al., 2014), while agricultural production is predominantly rainfed and highly sensitive to climate variability (Nyakudya and Stroosnijder, 2015). This implies difficult living conditions for rural people who depend on agro-pastoralism for their livelihoods (Pricope et al., 2013).

In Niger, the Sahara Desert covers ∼77% of the land area, with average annual rainfall ranging from 100 to 200 mm in the north and 500–600 mm in the south (World Bank, 2020). The other 23% of the land area in the southern part of the country is inhabited by people, 87% of whom depend on rainfed agriculture (Moussa et al., 2016). Degraded lateritic soils occupy more than 50% of the land surface and are prevalent in and around most of the villages in the 400–800 mm/year rain belt, and cost approximately 11% of the 2007 GDP of US$6.773 (Moussa et al., 2016). Niger's Human Development Index is 0.39 in 2019 (UNDP, 2020)[1], and land degradation is one of the main causes of poverty in the country (Orchard et al., 2017). It contributes to decreasing land productivity, the provision of terrestrial ecosystem services, and the benefits they provide for human wellbeing (Gerber et al., 2014). Most of the Niger's population depend heavily on the land for food and income and are thus vulnerable to land degradation. Women are more vulnerable to poverty as they are predominantly in the social groups of the ultra-poor (Ahmed et al., 2007), and land is normally bequeathed to sons (Doss et al., 2015). Given the importance of land for food security and cash income generation for Niger's rural households, one possible solution to overcoming poverty is the introduction of farming techniques without compromising the sustainability of crop production (Baidu-Forson, 1999). Therefore, instead of abandoning severely degraded lands, they might be rehabilitated (Moussa et al., 2016) and made available to rural women farmers, as it has been demonstrated in the literature that agricultural policies targeted at women are more likely to perform better in terms of household welfare outcomes (Doss, 2005; Quisumbing and McClafferty, 2006).

Since 2013, the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), in collaboration with Catholic Relief Services (CRS), has introduced the bio-reclamation of degraded land (BDL) technologies in 170 villages in the regions of Maradi and Zinder in Niger. The rationale for developing BDL systems is to bring these degraded lands back into production and transform them into productive soil. In practice, recovered lands are restored to Niger's largely marginalized rural women to improve their livelihoods through crop production. These technologies are implemented by women farmers' groups and depend on the types that fit the village/region where the system is implemented. In each village, a group of women was trained to build their capacity for cooperative management and traditional vegetable and fruit tree production in the BDL fields. The village chief provided the degraded lands to them, which were used to produce indigenous vegetables using BDL technologies. In Niger, similar to most countries in dryland areas, women do not have access to productive assets, including land, because they are not allowed to inherit the land. Therefore, introducing BDL technologies is seen to help women in the agricultural sector who mostly produce a short-duration cultivar of okra (*Abelmoschus esculentus*) introduced jointly by the World Vegetable Center (AVRDC) and ICRISAT.

However, since the introduction of BDL agricultural farming practices, less is known about their effect on women's wellbeing. To fill this gap in the literature, this study analyzes the determinants and impact of women's participation in the BDL system on their incomes. It extends the existing literature by revealing a new limiting factor of land-enhancing technology adoption by women and by showing that BDL is a pro-poor technology that is not equally beneficial to all rural farmers

1 HDI ranges from 0 to 1, with HDI = 1 being the highest level of development and 0 the lowest level.

(refer to Baidu-Forson, 1999). The remainder of this article is organized as follows. The "bio-reclamation of degraded lands program and its impact pathway in Niger" section briefly describes the BDL systems. The sections 3, 4 present the analytical framework, research design, and data. The section 5 presents the results and discussion. The final section presents the conclusions and policy implications.

2. Bio-reclamation of degraded lands program and its impact pathway in Niger

The BDL is an integrated system aimed at increasing food production and income of poor farmers (chiefly women) through the utilization of degraded lands for the production of rain-fed fruit trees and vegetables. The BDL improves soil fertility and harvested rainwater and is a successful tree-crop system. BDL combines indigenous water-harvesting techniques, application of organic matter, and planting of high-value trees and vegetables. The idea is to restore the productivity of the barren lateritic soils by using traditional water-harvesting planting techniques, like half-moons or zai pits, for the cultivation of high-value vegetables and trees. The impact on incomes and family nutrition makes the intensive labor investment worthwhile.

Degraded lands are sacrificed to break the surface crust. Micro-catchments (called demi-lunes) are built to catch and store runoff rainwater. The demi-lune is usually 2 × 3 m in size, but size can vary if necessary. The harvested water is stored in the soil for long periods and is utilized by a tree planted in the 40 × 80 cm ridge left in the center of the open side of the demi-lune to avoid waterlogging. Demi-lunes are usually spaced at 5 × 10 m. The area between the demi-lunes is occupied by planting pits known as "zaï" holes, which are holes 20 × 20 × 20 cm deep dug in the laterite. About 300 g dry weight of compost or manure is placed in the bottom of the zaï hole and is covered with a 5 cm layer of soil. The zaï holes are usually spaced at 0.5 × 1.0 m and also collect runoff water. The deeply placed compost in the hole results in extensive root growth, allowing the plant to exploit both water and nutrients. In addition, trenches are dug every 20 m down the slope to further harvest runoff water.

Trees are a major component of the BDL. They are much more resilient to droughts and can cope better with dry spells than annual crops. In a 200 m^2 plot, there are two "Pomme du Sahel" (*Ziziphus mauritiana*) trees and two *Moringa stenopetala* trees intercropped with traditional vegetables.

The most suitable vegetable crops are okra (*A. esculentus*) and roselle (*Hibiscus sabdariffa*). Other traditional leafy vegetables such as *Cassia tora* (*Senna obtusifolia*) can also be planted in the BDL system in addition to okra and roselle. Okra is a very important component of the diet in Niger.

The implementation of BDL technology promotes women's economic empowerment, improves micronutrient availability and access to nutrition, mitigates climate change, enhances women's access to land, improves soil fertility, and promotes soil conservation techniques in targeted communities (Pasternak et al., 2009; Moussa et al., 2016). The BDL development process consists of negotiating agreements with the village development committees, land commissions, women's groups, and land owners; then developing documents and legalizing lease agreements with signatures of land owners, the land commission, and women leaders; training CRS field agents and government extension staff in BDL, who in turn train women's groups; developing degraded land (physical components) through food for work; planting seedlings and annual crops at the onset of the rainy season; and finally, monitoring and supporting women's groups throughout the life of the project.

Owing to its simplicity and positive attributes, its potential for mass adoption is very high. The BDL reclaims the hidden potential of lateritic soils physically by increasing infiltration and water harvesting and biologically through the planting of hardy woody species and annual income generation. In doing so, the land is protected against further degradation while expanding the productivity of land and water, thus bringing economic benefits to women farmers. The BDL deals not only with desertification and climate change but also with women's empowerment (Fatondji et al., 2013). BDL is highly significant in regions where extreme pressure is exerted on scarce and fragile arable lands to produce more food for a rapidly growing population under climatic variation (Angrist and Pischke, 2009).

Figure 1 presents the impact pathway tracked in this study. The BDL program restores degraded land fertility and makes it available to women for cropping. Participation in this land-enhancing technology program is expected to increase the agricultural land area available for participant households and improve soil fertility and land productivity. Due to land availability and productivity improvements, household production and food availability are expected to increase. Households can increase the land area allocated to certain crops or produce new crops. Holding other things constant, an increase in production will improve women's income and food consumption. Therefore, women's self-worth, empowerment, and welfare, as well as household welfare, are expected to improve.

3. Conceptual framework

3.1. Decision to participate in BDL and selection bias

Suppose that women choose among T_i land-enhancing technologies, including BDL, a combination of soil scarification and indigenous water-harvesting methods in order to produce

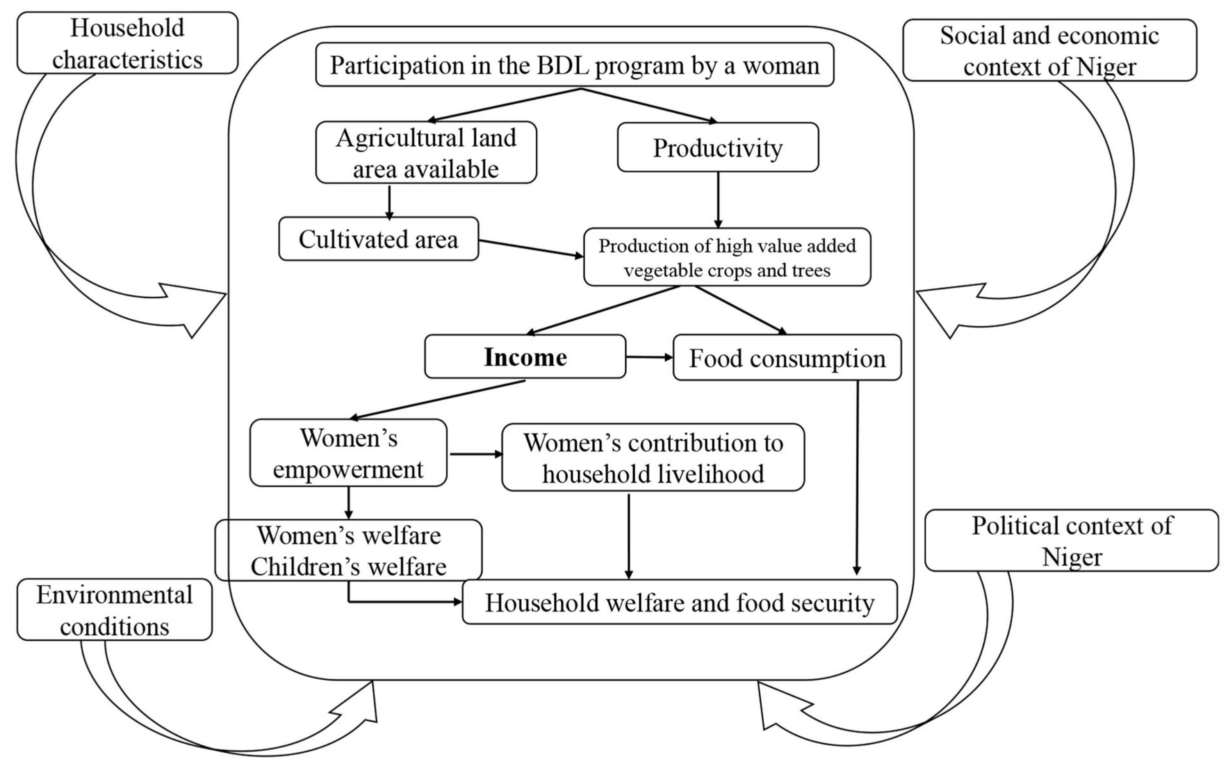

FIGURE 1
Impact pathway.

crops and maximize their consumption of food and non-food items utility, subject to some constraints on available resources and technologies. For woman i, the utility associated with participation or not in the BDL program is U_{iP} and U_{iN}, respectively. Participation in BDL is only known to the researcher, while the preferred net utility of women is known to them. The net utility can be represented by $U_i = U_{iP} - U_{iN}$ and expressed in a latent variable framework with respect to household characteristics as

$$T_i^* = X_i\alpha + \varepsilon_i\,, \qquad T_i = 1\left[T_i^* > 0\right] \tag{1}$$

where T_i is a binary variable equal to 1 for women who participate in BDL and 0 otherwise; X is a vector of observable factors that influence the decision to participate in BDL (participant, farm, and household characteristics); α is a vector of parameters to be estimated; and ε is the error term and is assumed to be normally distributed with mean zero and variance σ_ε^2. The term ε captures the measurement errors and unobserved factors that may influence the decision to participate in BDL. The probability of participating in BDL can be expressed as follows:

$$\Pr(T=1) = \Pr\left(T_i^* > 0\right) = \Pr\left(\varepsilon_i > -\alpha' X_i\right) = 1 - F\left(-\alpha' X_i\right) \tag{2}$$

where F denotes the cumulative distribution function of ε. In our estimation, Equation (2) is estimated using a probit model and presents the determinants of participation in BDL. For the impact of participation in BDL on income, suppose that women's income is a linear function of farm and household characteristics as follows:

$$Y_i = \beta Z_i' + \gamma T_i + \mu_i \tag{3}$$

where Y represents women's income; Z is a vector of the characteristics of participants, farms, and households; T is participation status whose probability is estimated in Equation (2); β and γ are parameters to be estimated; and μ is a random error term. All the factors in Z are observable variables and are declared by farmers. However, unobserved variables, such as women's managerial abilities, innate technical skills, risk behavior, and social networking, may also influence the dependent variable and are captured in the error term μ. The estimation of Equation (3) with ordinary least squares can cause bias because of the possible correlation between the two error terms ($corr(\varepsilon, \mu) \neq 0$). In other words, a potential selection bias may occur when the unobservable factors (μ) of Equation (3) influence the unobservable factors (ε) of Equation (1). This selection bias problem is overcome in a randomized control trial design, in which women are assigned randomly to participant and control groups such that participation in the program is the only difference between participants and non-participants (Heckman and Vytlacil, 2005; Angrist and Pischke, 2009; Asfaw et al., 2012; Abdulai, 2016). However, women's participation in the BDL program is a non-random experimental design, and participants self-selected themselves into the program, which gives rise to a selection bias problem. In this case, propensity score matching, which is commonly used in impact assessment frameworks, can be used to address the selection bias problem. A major deficiency of this approach is that it fails to account for unobservable factors (Heckman et al., 1998; Abadie and Imbens, 2006). Another approach is the use of instrumental variables to assign individuals to participant and control groups using a two-stage estimation technique. However, the instrumental variable approach generates heteroskedastic residuals (Lokshin and Sajaia, 2004) that cannot allow consistent standard error estimation without cumbersome adjustments (Abdulai, 2016). Lokshin and Sajaia (2004) proposed using a full information maximum likelihood technique as a consistent solution. This approach overcomes the two-stage estimation and allows for the simultaneous estimation of the determinants (Equation 1) and impact (Equation 3) while accounting efficiently for both observable and unobservable factors. This estimation technique was implemented through endogenous switching regression (ESR).

Endogenous switching regression, developed by Lokshin and Sajaia (2004), was used in this study to estimate the determinants and impact of participation in the BDL program. This approach has been used in several empirical impact evaluation studies to address selection bias (Kassie et al., 2014; Kleemann et al., 2014; Alem et al., 2015; Debela et al., 2015; Mmbando et al., 2015; Abdulai, 2016). In the first stage, Equation (1) was estimated, and the determinant factors of participation in BDL were identified. In the second stage, Equation (3) was used to determine the impact of participation in BDL. Two separate regimes for participants and non-participants were specified as follows:

$$Y_1 = Z_1\beta_1 + \mu_1 \qquad \text{if } T_i = 1 \tag{4a}$$
$$Y_0 = Z_0\beta_0 + \mu_0 \qquad \text{if } T_i = 0 \tag{4b}$$

where Y_1 and Y_0 represent the income of the participants and non-participants, respectively. The variable Z is a vector of explanatory variables, β is a vector of model parameters to be estimated, and μ is the error term that is assumed to be normally distributed. The ESR structure is such that Equations (1) and (3) overlap and use the same list of explanatory variables, meaning that vectors X and Z contain the same list of variables. However, for estimation purposes, at least one variable, X, should be dropped from Z. The missing variable in the outcome equation acts as an identifying instrument (Di Falco et al., 2011). To be valid, it should influence the decision to participate in BDL but not directly influence the income. Institutional support, estimated by the number of years of partnership between Savings and Internal Lending Communities (SILC), was used as an instrumental variable. This variable was expected to influence participation in BDL but not directly the income. Conceptually, participation in the BDL program relates to its relationship with SILC. Vector Z in Equations (4a) and (4b) accounts only for selection bias due to observable factors. ESR uses an omitted variable problem framework to address selection bias due to unobservable factors. The inverse Mills ratios or selectivity terms (λ_1 and λ_0) from the selection equation and the covariance terms ($\sigma_1$and σ_0) are substituted into (4a) and (4b) to obtain Equations (5a) and (5b) as follows (Heckman, 1979):

$$Y_1 = Z_1\beta_1 + \sigma_{1\varepsilon}\lambda_1 + \epsilon_1 \qquad \text{if } T_i = 1 \tag{5a}$$
$$Y_0 = Z_0\beta_0 + \sigma_{0\varepsilon}\lambda_0 + \epsilon_0 \qquad \text{if } T_i = 0 \tag{5b}$$

where ϵ_1 and ϵ_0 are error terms with conditional zero means. The selectivity terms (i.e., λ_1 and λ_0) in Equations (5a) and (5b) are correct for selection bias owing to unobservable factors. The expected income of women who participated in the BDL program and the expected income of the counterfactual hypothetical cases in which participants did not participate can be predicted from the estimated model. The change in women participants' income due to participation in BDL can then be estimated by comparing expected income and their counterfactuals, as indicated in Table 1.

3.2. Survey design and data

This study was conducted in the regions of Maradi and Zinder in Niger (Figure 2). The Maradi region is in the south-central part of Niger. It covers an area of 41,796 km^2, and its population was estimated to be 206,414 inhabitants in 2012. Approximately 72% of the Maradi area is agricultural land, 25% is pastoral land, and 3% is forest land. Two types of climates were observed in the region: a Sahelian climate in the north, characterized by an average annual rainfall between 200 and 300 mm, and a Sahelo-Sudanese climate in the south, characterized by an average annual rainfall between 500 and 600 mm. The Zinder region is a desert located between 12°50' and 16°30' latitude north and 7°30° and 13° longitude east. It covers an area of 145,430 km^2 with an estimated population of 321,809 in 2012. The rainfall decreases from south to north, with an average of ~425 mm.

BDL technologies were spread by CRS, an international NGO supported by the ICRISAT under a joint project. The survey was implemented in twelve districts, including nine districts in the Kantche region of Zinder and three districts in the Mayahi region of Maradi. The design of this study is shown in Figure 3. Two-stage selection sampling was used. At the village level, only villages with SILC groups were considered. Among the SILC villages, some women participated in the

TABLE 1 Conditional expectations and treatment effects.

	Participants' profile	Non-participants' profile	Treatment effects
Participants	(a) $E(Y_1\|T=1)$	(c) $E(Y_0\|T=1)$	ATT
Non-participants	(d) $E(Y_1\|T=0)$	(b) $E(Y_0\|T=0)$	ATU
Heterogeneity effects	BH1	BH2	TH

(a) and (b) represent the conditional expectations, and (c) and (d) represent the counterfactual hypothetical cases.

$(a) = X_1\beta_1 + \sigma_{\epsilon_1\varepsilon}\lambda_1$ (6)

$(b) = X_0\beta_0 + \sigma_{\epsilon_0\varepsilon}\lambda_0$ (7)

$(c) = X_1\beta_0 + \sigma_{\epsilon_0\varepsilon}\lambda_1$ (8)

$(d) = X_0\beta_1 + \sigma_{\epsilon_1\varepsilon}\lambda_0$ (9)

ATT = average treatment on treated [average effect of participation in BDL on participants (a-c)].

$ATT = E(Y_1|T=1) - E(Y_0|T=1) = X_1(\beta_1 - \beta_0) + \lambda_1(\epsilon_1\varepsilon - \epsilon_0\varepsilon)$ (10)

ATU = Average treatment on untreated [average effect of participation in BDL on non-participants (d-b)].

$ATU = E(Y_1|T=0) - E(Y_0|T=0) = X_0(\beta_1 - \beta_0) + \lambda_0(\epsilon_1\varepsilon - \epsilon_0\varepsilon)$ (11)

BH1 = heterogeneity effects for participants (a-d).

BH2 = heterogeneity effects for non-participants (c-b).

TH = (ATT – ATU), transitional heterogeneity.

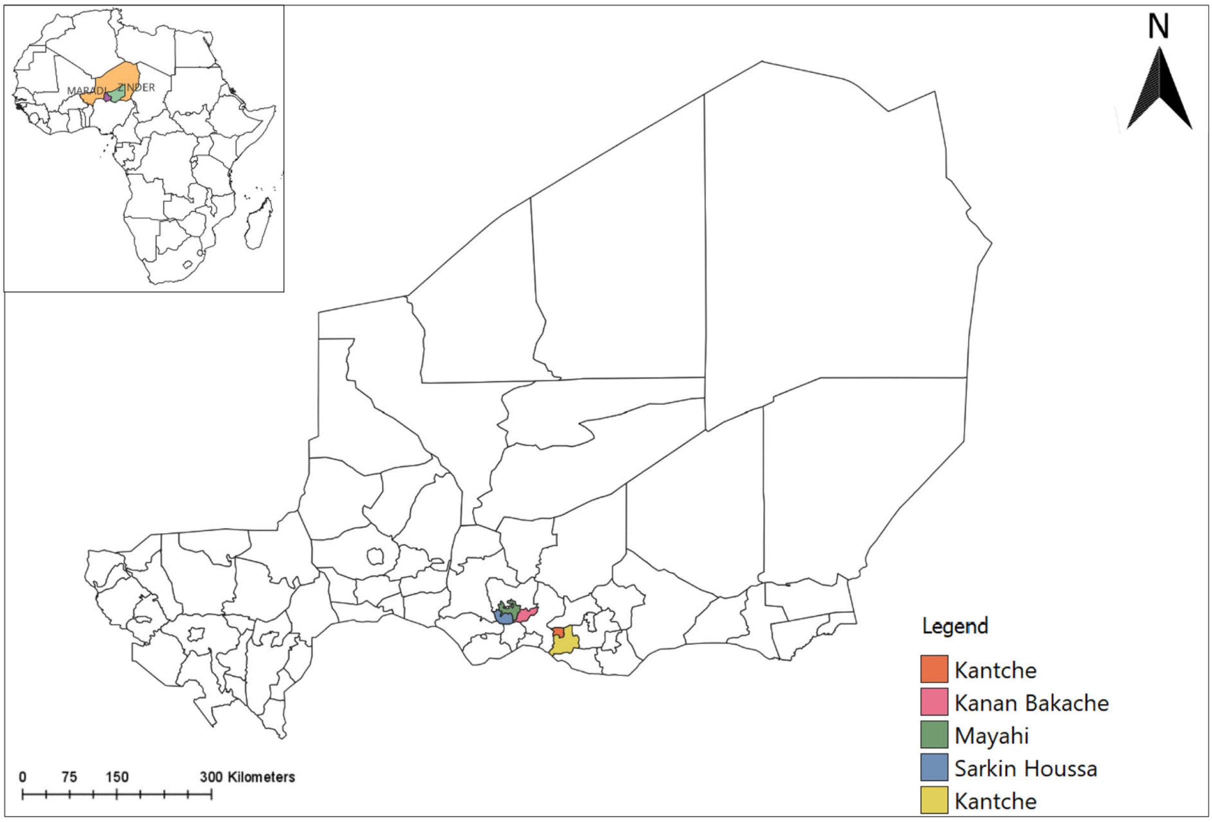

FIGURE 2
Study area.

BDL program, while others did not. A total of 27 villages were randomly selected, including twenty-five BDL villages and two non-BDL villages. Only women were targeted at the farm level. In total, 1,205 women farmers were randomly selected: 28% in the Maradi region and 72% in the Zinder region. The sample included 826 participants in the BDL program (69%) and 379 non-participants (31%). Among the non-participants, 333 were from BDL villages, and 46 were from non-BDL villages.

Data were collected in 2015 using focus group discussions with women's groups to identify and describe the technologies

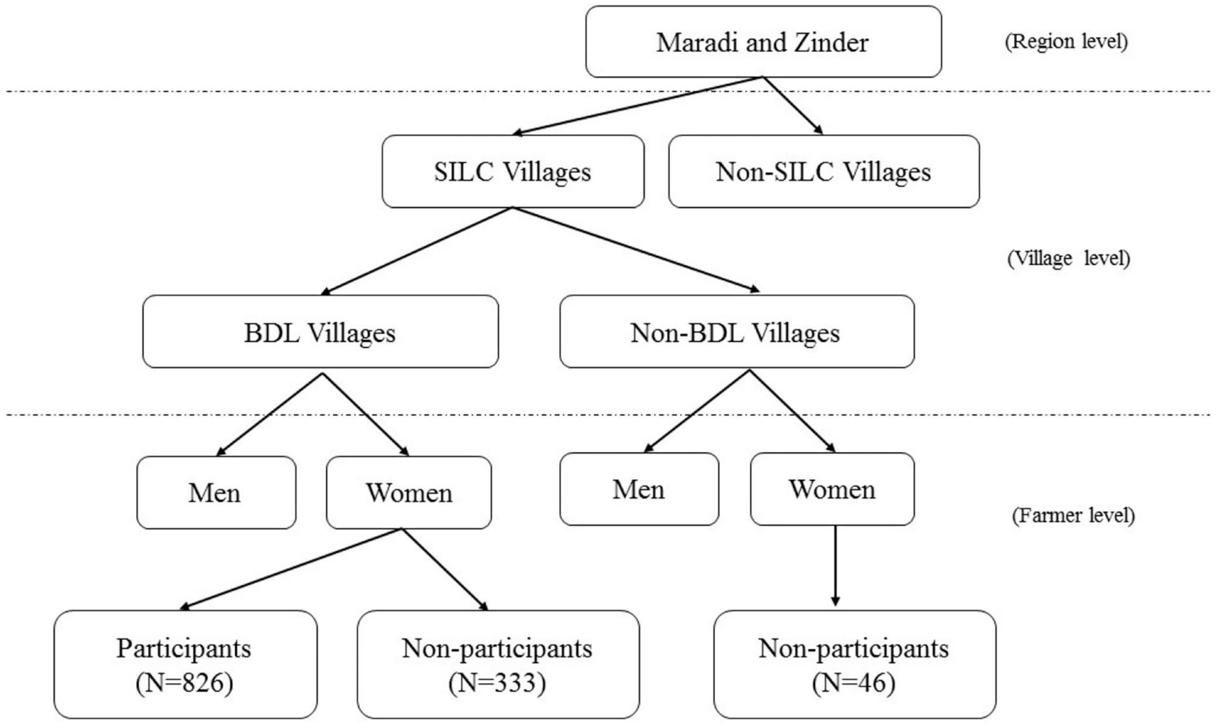

FIGURE 3
Research sampling design.

and evaluate the constraints and opportunities of BDL. In addition, individual questionnaires were used to collect socioeconomic and demographic data, as well as farmers' household livelihoods.

3.3. Outcome variable

A woman's annual income in FCFA[2] was used as a proxy for the women's welfare indicator. Income data were collected for the 12 months preceding the survey. It was self-reported by the respondents based on income from different income-generating activities per month and then aggregated to an annual scale. On average, participants in the BDL program received 77,039 FCFA per year compared to 80,732 FCFA for non-participants. This difference was not statistically different from zero.

3.4. Exploratory variables

Several paradigms based on factors influencing decision-making have been used in the literature to explain farmers' decisions to adopt new agricultural technology (Negatu and Parikh, 1999; Moumouni et al., 2013). Three categories of factors are likely to influence the decision to adopt new agricultural technologies: the characteristics of the technology, the characteristics of farmers and their households, and economic and institutional factors. In this study, we combined household characteristics, economics, and institutional factors to explain the decision to participate in BDL and the impact assessment. The independent variables used in the models are listed in Table 2. For convenience, the variables were classified into five categories, namely, participant characteristics, household characteristics, household welfare, institutional support, and location.

Table 2 shows that participants and non-participants are statistically different on five characteristics, including household size, income before participation in the BDL program, number of livestock (chickens) in the household, and relationship with SILC. On average, there were eight persons in participant households against seven in non-participant households. Before the implementation of the BDL program, non-participant households had more FCFA 12,630 in annual income than participant households. In addition, on average, there was one more livestock (chicken) in non-participant households than in participant households. Participants had a long-term relationship with SILC: 6 years of collaboration against about 1 year for non-participants. About 21% of participants lived

2 US$1 = 588.23 in 2015.

TABLE 2 Data description.

Variable	Participant		Non-participant		Difference
	Mean	SD	Mean	SD	
Outcome variable					
Income after BDL (FCFA[a])	77,039	147,730	80,732	119,164	−3,693
Participants characteristics					
Age of participant	37.11	12.80	35.79	13.42	1.3
Education (years of schooling)	0.84	1.60	0.72	1.37	0.13
Household characteristics					
Sex of household head (dummy, one for female)	0.94	0.25	0.92	0.28	0.02
Age of household head (years)	48.71	13.54	47.85	14.70	0.86
Household size (number of persons)	8.35	7.35	7.37	5.13	0.98**
Number of women in the household	1.64	2.52	1.50	1.61	0.14
Household wealth					
Income before BDL (FCFA[a])	50,643	86,198	63,275	104,109	12,631**
Available area for the household (ha)	0.91	2.73	1.05	1.31	0.13
Number of sheep	0.83	1.47	0.89	1.60	0.06
Number of chickens	2.08	4.02	3.21	6.26	1.13***
Institutional support					
Number of years of collaboration with SILC and PASAM	6.28	2,69	0.63	2.79	5.64***
Location					
Living in Maradi region (dummy, one for Maradi)	0.21	0.41	0.44	0.50	0.23***

***Indicates significance at 1% level.
**Indicates significance at 5%.
[a]US$1 = 588.23 in 2015.

in the Maradi region. The proportion of non-participants in that region was two times than that of participants. These five variables are included in the model to control for selection bias.

4. Results

The section 4.1 highlights the model specification and validity test. The section 4.2. presents the determinants of participation in land-enhancing technology, and finally, the impact of BDL participation is discussed in more detail.

4.1. Model validation

Table 3 presents the results of the selection and outcome equations jointly estimated using the full information maximum likelihood approach.[3] Selection equation (Equation 1) is reported in column 1, while the outcome equations of participants (Equation 4a) and non-participants (Equation 4b) are shown in Columns 2 and 3, respectively. As indicated in the conceptual framework, at least one variable of the selection equation should be removed from the outcome equation for estimation. The Institutional support variable, shown by the number of years of collaboration between SILC, is conceptually relevant as an instrumental variable in the selection equation. This variable significantly affects the decision to participate in the BDL program, but there is no significant relationship between this variable and the income model. In addition, the sex and age of household heads are not statistically significant in outcome equations, and they negatively affect the stability of the model. This implies that these variables were consistently estimated in the other explanatory variables (Wooldridge, 2010) and were removed from the selection equation accordingly.

The likelihood-ratio tests for joint independence of the three equations indicate that the null hypothesis of no correlation between selection and outcome equations was rejected at a 1% level of significance. The selection and outcome equations are highly dependent and must be estimated jointly. The

3 The full information maximum likelihood was estimated using command *movestay* of Lokshin and Sajaia (2004).

TABLE 3 Full information maximum likelihood estimation of endogenous switching regression.

Variables	Participation to BDL (Equation 1)		Income of participants (Equation 4a)		Income of non-participants (Equation 4b)	
	Coef.	SE	Coef.	SE	Coef.	SE
Income before BDL (FCFA)	0.00***	0.00	1.21***	0.16	0.78***	0.20
Household size (number of persons)	0.03***	0.02	1,335.99	661.04	−1,463.88	390.71
Education level (number of years of schooling)	0.11	0.08	1,641.42***	91.86	616.74	1,419.48
Available land area for the household (ha)	0.10	0.09	−1,882.77**	987.05	−7,194.5***	1,867.12
Age of participant (years)	0.02***	0.01	98.90	158.36	83.42	125.47
Living in Maradi region (dummy, one for Maradi)	−0.64***	0.10	996.13	3,824.64	−6,221.59	3,789.82
Number of sheep in the household	0.01	0.02	−608.86	1,570.55	3,050.92***	171
Number of chicken in the household	0.00	0.00	−34.91	69.93	1,353.70	1,697.21
Number of women in the household	−0.12***	0.04	−1,139.99	119.50	4,855.93***	993.14
Number of children under 5 years old	−0.01***	0.00	1,646.66	3,334.04	1,828.55	2,291.80
Sex of household head (dummy, one for male)	−0.53***	0.09				
Age of household head (years)	−0.02**	0.01				
Institutional support (number of years of collaboration with SILC)	0.65***	0.12				
Constant	−1.34***	0.09	−8,165.9***	1,394.41	27,273.6***	5,586.74
$\ln\sigma_1$			11.56***	0.01		
ρ_1			0.79***	0,03		
$\ln\sigma_2$					11.04***	0.00
ρ_2					−0.00	0.05
Log likelihood: −14,096.76						
Wald test of independence equations: $Chi^2(1) = 168.63$***						
Number of observations = 1,089						

***, **Indicate significant level at 1 and 5%, respectively.

correlation coefficient rho (ρ) between the selection equation of the BDL program and the income equation for participants was statistically significant. This indicates that selection bias due to unobservable factors in participation in the BDL program, and the use of ESR, which accounts for both observable and unobservable factors, is relevant and appropriate for this study (Lokshin and Sajaia, 2004). The positive sign of ρ_1 between the equation selection and participant income suggests a negative selection bias. In other words, women with higher incomes are less likely to participate in the BDL program. Coefficient ρ_2 between the selection equation and the non-participants equation is negative, null, and non-significant, suggesting that non-participants are better off in their non-participant status. Hypothetical participation in the BDL does not improve actual non-participant income. A non-participation regime is best for non-participants.

4.2. Determinants of participation in BDL program and income

Following Abdulai (2016), the results of Equation (1) in Column 1 of Table 3 can be interpreted as a normal probit. A total of nine factors were found to be determinants of participation in the BDL program. Specifically, income level before participation in BDL, household size, age of participants, location, number of women in the household, number of children under 5 years old, sex of household head, age of household head, and institutional support are factors that explain participation in this land-enhancing program. The coefficients of institutional support, age of participants, household size, and income level before the BDL program positively affected participation in the program. In other words, these variables increase the probability of women participating in the use of land-enhancing technologies. In contrast, the number of women in the household, number of children under 5 years old, living in the Maradi region, sex, and age of the household head negatively affected participation and likely reduced the probability of women participating in the BDL program. Living in the Maradi region or in a household headed by a woman limits the likelihood of participating in the BDL program. Similarly, the probability of participating in BDL decreases when the number of women present in the household, children under 5 years old, or the age of the household head increases.

Regarding the income impact results of Equations (4a) and (4b) in Table 3, two similarities and three differences can be observed between the participant and non-participant models. In terms of similarity, income before BDL has a positive and significant coefficient, both in Equations (2) and (3). Similarly, the land area available for the household has a negative and significant coefficient in Equations (2) and (3). In terms of the difference between the two equations, the number of years of education positively affects the income of participants but has no effect on non-participant income. The number of chicken heads and the number of women in the household positively affected the income of non-participants but did not affect participants' income.

4.3. Impact of participation in BDL program on income

Table 4 presents an estimation of the impact of participation in BDL on women's annual income. This table contains four key pieces of information such as the conditional income of participants and non-participants, counterfactuals for participants and non-participants, treatment effect on participants (ATT) and non-participants (ATU), and treatment effect in the percentage of potential outcome mean (POM).[4] On average, women participating in the BDL program have about 75,353 FCFA (US$151).[5] If participants had not participated in the BDL program, they would have an average annual income of 66,065 FCFA (US$132). Therefore, there is a difference of 9,288 FCFA (US$19), which is a consequence of participation in the BDL program. This gain represents an annual income increase of 14% due to participation in the BDL program. For non-participants, the average annual income was 77,482 FCFA (US$155). If the non-participants had participated, their average income would be 59,114 FCFA (US$118). This represents a loss of 18,368 FCFA (US$37). In other words, if the non-participants had participated in BDL program, their income would have been reduced by 31%, suggesting that non-participants are better off in their current situation.

TABLE 4 Income conditional expectation and effects of participation in BDL.

	Participant women	Non-participant women
Income with participation (FCFA[a])	75,352.84*** (3,732.49)	59,114.16*** (6,973.23)
Income with non-participation (FCFA[a])	66,064.82*** (2,517.75)	77,481.74*** (4,148.80)
ATT (FCFA[a])	9,288.02*** (1,580.7)	–
ATU (FCFA[a])	–	−8,367.61*** (3,629.44)
Treatment effects (% of POM)	14.06	−31.07

***Significant, respectively, at 1, 5, and 10%.
Robust standard error in parenthesis.
POM stands for potential outcome mean.
[a]US$1 equaled 588.23 FCFA in 2015.

5. Discussion

The objective of this study was to analyze the determinants and impact of participation in a BDL program on rural women's income. Land-enhancing technology has targeted only rural women in degraded land areas in Niger. The decision to participate in the program was voluntary. The findings indicate that, *ceteris paribus*, the likelihood of participating in the BDL program is positively and significantly correlated with institutional support, age of participants, household size, and annual income before participation in the program. In contrast, the number of women in the household, the number of children under 5 years old living in the Maradi region, sex, and age of the household head negatively and significantly influenced the decision to participate. Previous studies on the determinants of the adoption of agricultural technology have shown the importance of institutional support in adoption decisions. By analyzing factors influencing the adoption of land-enhancing technologies in the same country, Niger, Baidu-Forson (1999) concluded that improving technical support, which demonstrates the risk reduction capacities of land-enhancing technologies, stimulates the adoption of these technologies. Mazvimavi and Twomlow (2009) conducted a similar study in Zimbabwe and reported the significant influence of institutional support on the adoption intensity of land-enhancing technologies. NGO staff have become an important source of technical support in promoting technology and working closely with farmers.

The relationship between rural farmers' ages and the adoption of new agricultural technologies is not constant in the literature. Previous studies have reported the negative impact of

4 Treatment effect in percentage of POM = impact (income gain due to participation)/the potential income she would obtain if she did not participate in BDL program.

5 US$1 = 499 FCFA during the period of the study in 2015.

farmers' age on the adoption of land-enhancing or conservation technologies (Baidu-Forson, 1999; Abdulai, 2016). The trend is such that one can infer that older farmers are less willing to adopt improved land-enhancing technologies. This effect can also be mixed, as concluded by Lapar and Pandey (1999), who studied the adoption of upland soil conservation technologies in the Philippines. The special case of women in the adoption of land-enhancing technologies has not yet been discussed in the literature. In this study, both the age of the household head and the age of the women participating were used in the estimations. The effect of the age of the household head is negative, significant, and consistent with the literature. Regarding the age of the participants, the likelihood of participation in the BDL program increased when the participant's age increased. This result can be explained by the fact that farmers become more skillful, through learning-by-doing, and more risk averse as they become older (Mazvimavi and Twomlow, 2009).

A negative and significant relationship between the sex of the household head (male) and the likelihood of participating in the BDL program was found, which is in line with previous studies. Mazvimavi and Twomlow (2009) concluded that male-headed households were more likely to adopt technology. The most convincing explanation for the results of this study can be deduced from Ahmed et al. (2009) and Ahmed et al. (2014). Ahmed et al. (2014) showed that the welfare of women and girls within a rural household depends on the sex of the household head. The welfare of women and girls may be lower than that of their male counterparts in households headed by men. Less food and lower-quality food consumption have been reported for women in households headed by men (Ahmed et al., 2009). Thus, the livelihood of women living in female-headed households is better than those living in male-headed households. This finding justifies why women in female-headed households are less willing to participate in the BDL because they are less needy. In addition, female household heads in rural areas of sub-Saharan Africa are relatively old (57 years old in this study) and generally widowed (67% in this study). In addition, it is uncommon to find many adult females in female-headed households. Thus, female-headed households have one adult woman in general who is old and not open to participate in an agricultural innovation program like BDL.

The location of farmers is important in the decision-making process to adopt land-enhancing technology. This study revealed a significant relationship between the location and the likelihood of participating in the BDL program. Living in the Maradi region reduces the probability of participating in the BDL program, while living in the Zinder region increases the probability of participating in the BDL program. Baidu-Forson (1999) indicated that the probability and intensity of the adoption of land-enhancing technologies are likely to be high in locations that have large percentages of degraded farmlands. This is the case in the Zinder region, where land degradation is an important challenge for enhancing land productivity (Fatondji et al., 2013). Another relevant factor for participating in the BDL program is household size. The effect on the decision to participate in BDL was positive (Table 3). In addition, the number of children under 5 years of age had a negative and significant effect on the likelihood of women participating in the BDL program. The number of children under 5 years of age is then a limiting factor for women's participation in the BDL program, as women are responsible for taking care of children. This finding extends the existing literature on the determinants of new agricultural technology in general and land-enhancing technologies. This suggests that land-enhancing technologies may not target women who have children under 5 years of age unless special arrangements are made to give them time to take care of their children.

Although this study, to the best of our knowledge, is the first attempt to estimate the economic impact of the BDL program and the impact of land-enhancing technology exclusively on women's welfare, some previous studies have already provided an overview of the results trend. Similar studies have reported a positive impact of the use of land-enhancing technologies on the livelihoods of users. Moussa et al. (2016) analyzed the economics of land degradation and improvement in Niger and concluded that every US dollar invested in taking action returns about US$6. Abdulai (2016) estimated the impact of the adoption of conservation agriculture technology in Zambia and found that the adoption of this technology contributed significantly to the reduction of household poverty. Regarding the findings on the impact of participation in BDL in this study, the following three main results were obtained: participation in BDL has a positive impact on participants' income (+14%); non-participants had no interest in participating as they would lose 31% of their income; and the impact of participation in BDL widely varies across regions. Non-participants were relatively richer than participants. For example, before the advent of BDL, the income of non-participants was higher than that of participants by 25% (Table 2). In addition, non-participants had more livestock than participants. Therefore, it can be inferred that BDL is a pro-poor technology that is not beneficial to all women farmers. This study makes a critical contribution to the literature on land-enhancing technologies. It suggests that the impact of land-enhancing technologies, such as BDL, is closely linked to spatial, economic, environmental, temporal, and cultural contexts (Sallu et al., 2010; Orchard et al., 2017). Accordingly, land-enhancing technologies should target locations that have large percentages of degraded farmlands (Baidu-Forson, 1999) and the poorest farmers.

6. Conclusion and policy implications

In the dryland areas of Sub-Saharan African countries, land degradation is a major constraint that leads to a reduction in arable land availability, a decline in agricultural productivity, and, consequently, a rise in poverty. Niger is one of the most affected countries in West Africa, where most of the rural population depends heavily on agriculture and livestock for income. Women farmers are the most vulnerable to poverty because of their limited access to land for farming. The BDL technology was introduced in 2013 to restore degraded land and make it available for women to contribute to their empowerment. This study investigated the adoption of this technology and its impact on women's purchasing power. To control for observed and unobserved factors, ESR was used to estimate the participation effect.

The findings show that factors including institutional support, age of participants, and household size positively affect the likelihood of women using the BDL technology. In contrast, factors such as the sex of the household head, age of the household head, location (Maradi region), and the number of children under 5 years old tend to reduce the probability of using the technology. Furthermore, it was shown that adoption of the technology led to an income increase of 14% for users, while non-users (less poor than users) would lose about 31% of their income in the case of adoption. In addition, the impact of adopting BDL technology varies across locations.

This study has two main policy implications. First, land-enhancing technologies, in general, and BDL technology should not target women who are caregivers of children under 5 years of age unless special arrangements are made to give them time to take care of their children. Taking this recommendation into account would stimulate the adoption of land-enhancing technologies by women. Second, land-enhancing technologies should target locations with large percentages of degraded farmlands, especially those of the poorest rural farmers. Since land-enhancing technologies may have a dynamic impact, an area of further study would be the use of panel data to capture the change across years.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Ethics statement

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. Written informed consent from the participants was not required to participate in this study in accordance with the national legislation and the institutional requirements.

Author contributions

AS: conceptualization, methodology, software, validation, formal analysis, data curation, writing—original draft, and writing—review and editing. JQ: conceptualization, data collection, and coordination. AB: methodology, software, validation, formal analysis, data curation, and writing—original draft. JL: methodology, validation, formal analysis, and writing—original draft. DF: conceptualization, data collection, and technology implementation. LD: formal analysis, data curation, and writing—original draft. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Insights into land size and productivity in Ethiopia: What do data and heterogenous analysis reveal?

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This study investigates whether the historical inverse relationship (IR) between land (farm and plot) size and productivity holds for Ethiopia farms. The study uses plot-level and household-level data from the three waves of the Ethiopia Socioeconomic Survey. The main finding, which confirms previous studies, is that the plot-size IR holds when productivity measurement is based on self-reported yields. However, the effects were reversed when we used crop-cut yields. Including labor inputs significantly reduces the magnitude of the coefficients on land size but not the sign. Finally, the quantile regression reveals interesting findings. These are: (1) a strong positive effect of farm (and plot) size on productivity; (2) the magnitude of the effect decreases monotonically with quantile; (3) farm size displays a robust negative impact on gross revenue and the magnitude of the effect increases (in absolute terms) monotonically with quantiles; (4) the effect of farm (and plot) size on productivity decreases in magnitude when we control for labor input; (5) the IR between farm (and plot) size and total and family labor was negative and significant and the effect increases (in absolute terms) monotonically with quantiles.

KEYWORDS

agricultural productivity, land-size, farm-size, inverse relationship, quantile regression, Ethiopia, Sub-Saharan Africa

Introduction

Sub-Saharan Africa (SSA) is home to 40 percent of the world's poorest people (Ferreira et al., 2016), and a significant majority of them rely on agriculture as a source of livelihood and income-generating activity (Livingston et al., 2011). With most people deriving their livelihood from agricultural work, understanding the level and the role of agricultural productivity in reducing poverty and increasing economic development is essential. For instance, Irz et al. (2001) show that a 10 percent increase in land productivity leads to a 7 percent decrease in Africa's poor people. Byerlee et al. (2009) reveal that the countries with the highest agricultural growth per worker experienced the most significant rural poverty reduction rate. Several other studies (e.g., Mellor, 1999; Thirtle et al., 2001; Ravallion and Chen, 2007; Schneider and Gugerty, 2011) confirm a positive relationship between agricultural productivity growth and poverty alleviation. Thus, there are multiple pathways through which increases in agricultural productivity can reduce poverty, including income changes, employment generation, rural non-farm multiplier effects, and a decline in food prices (Bresciani and Valdés, 2007; Schneider and Gugerty, 2011). Beyond poverty reduction, agricultural growth has been identified as enormously beneficial to other crucial aspects of development, namely nutrition: a 10% increase in agricultural GDP per capita reduces child stunting by 9.6% (as opposed to 8.4% for non-agricultural; Mary et al., 2017).

In recognizing the potential role of agricultural productivity, especially land productivity, in overcoming poverty and spurring economic development, the question is whether smallholdings[1] are the fundamental units. In other words, to what extent the smallholdings maybe focus on economic growth when the policymakers in developing economies want to make economic progress? If the smallholdings are the focal point, then to what extent does the historical inverse relationship (IR) between land size (i.e., farm size or plot-size) and land productivity still hold, particularly in SSA? For decades, it has been widely accepted that there is an inverse relationship between farm size and productivity in many developing economies (often referred to as farm-size IR) (Chayanov, 1926; Sen, 1962; Binswanger et al., 1995; Vollrath, 2007; Carletto et al., 2013; Larson et al., 2013; Kagin et al., 2015; Julien et al., 2019; Wassie et al., 2019). Such IR implies that smaller farms (plots) are more productive than larger ones. Therefore, breaking small farms into smaller units (land fragmentation) may further enhance productivity. This empirical finding has received considerable attention from policymakers in developing countries because it could motivate land redistribution from medium-large landowners to more productive small peasants. It constitutes an opportunity to achieve both equity and efficiency. In fact, through the same land reform instrument that promotes smallholders, it would be possible to support the welfare of (relatively) poor households and stimulate aggregate productivity (Cornia, 1985).

However, the IR hypothesis has increasingly been questioned, and several studies have found evidence to the contrary (Newell et al., 1997; Fan and Chan-Kang, 2005; Otsuka et al., 2016). Other studies have shown a U-shaped relationship between farm-size and productivity (Kimhi, 2006; Foster and Rosenzweig, 2017; Jayne et al., 2019; Muyanga and Jayne, 2019). Although most of these studies focus on South and Southeast Asia, their policy implications were worldwide, particularly in Africa. Indeed, many African governments have used the inverse relationship between size and productivity findings to re-evaluate their agrarian policy. Other governments have gone one step further by promoting a land consolidation policy (instead of land fragmentation) and supporting the development of medium and large-scale farms to improve agricultural productivity and transform countries' agricultural sectors.

Among these countries, one could quickly mention Ethiopia, which seems to have been subject to land grabs in an attempt to transform the effectiveness of agricultural production (Tura, 2018). Recall that the *Derg* regime in 1975 nationalized all rural land, giving land use rights to the smallholders. In the 1990s, the government of Zenawi argued that state land ownership protected smallholders from the landholding class, provided social security, and reduced urban migration (Lavers, 2018). However, increased urbanization and rapid population growth have led to diminishing landholdings. Additionally, land insecurity reduced land investment, and as a result, agricultural productivity has suffered (Deininger and Jin, 2005). Accordingly, this study's main objective is to test the inverse relationship between productivity and land size at both plot and farm (holding) levels for small-medium farm households in Ethiopia. The study uses two measures of productivity, namely yield and gross revenue. We use yield when we analyse plot-size and productivity relationships. However, we use gross revenue when investigating the relationship between farm size and productivity. We also use two yield measurements, self-reported and crop-cut,[2] to tease out any biases in reporting and mismeasurement.

The paper is organized as follows. The following section reviews the main strands of literature related to the land-size (particularly farm-size) and productivity relationship. Section Empirical framework describes the econometric models and the data. Section Results and discussion presents and discusses the results. The final section summarizes the contributions of the analysis to the literature and discusses the findings' policy implications.

Literature review

The controversy about an inverse relationship (IR) between land-size and productivity has been one of the enduring debates in the development and agricultural economics literature. Although the inverse plot-size and farm-size relationships are closely related, more attention has been given by researchers and policymakers to farm-size IR because of its controversial implications for land reform. For instance, Chayanov (1926) first discovered farm-size productivity inverse relationships among Russian farms. In India, Sen (1962) found that smaller farms employed more labor per hectare, and farm productivity decreased with farm size. In India's case, Eswaran and Kotwal (1986) show that small farms have a higher output per hectare than large farms because of the increasing marginal cost of supervision. Small farms mostly rely on family labor and hence have advantages in labor supervision. A study by Larson et al. (2013) using farm household survey data from four countries (Malawi, Tanzania, Kenya, and Uganda) concludes a negative relationship between farm size and output. The farm-size IR has been observed in many developing countries, including countries in Africa (see Barrett, 1996; Kimhi, 2006; Carletto et al., 2013; Larson et al., 2013; Kilic et al., 2017; Khataza et al., 2019), South Asia (see Heltberg, 1998; Benjamin and Brandt, 2002; Gautam and Ahmed, 2019), and Latin America (see Kagin et al., 2015).

On the contrary, several other studies have revealed a positive relationship between land size and productivity. For instance, Obasi (2007) found that farm size is positively related to agricultural productivity in Nigeria. The author argues that a positive relationship could be due to low-quality inputs used by smallholders. Kimhi (2006) examined the relationship between farm size and maize output in Zambia. Treating plot size as exogenous, the author found a positive and significant relationship between maize yield and plot size. Additionally, the author found the economies of scale as dominant throughout the plot-size distribution. However, the author found an inverse relationship between plot size and maize yield when treating plot size as an endogenous variable (farmer's self-selection into maize production). Similarly, Chen et al. (2011) found that the

1 Smallholdings are subsistence or semi subsistence farms with limited or no market participation (i.e., they produce only for household consumption or they have limited engagement with markets).

2 Crop cut is a technique for estimating crop yield on the basis of the sampling of small subplots within cultivated fields. The method involves the random demarcation of a plot of a specified size and shape, harvesting the produce from the plot, and threshing, winnowing and drying the produce to determine its dry weight. The harvest of that subplot is used as the plot's yield, and it is assumed that any error is independent of the total plot-size. For an in-depth description of crop-cut, readers are directed to Gourlay et al. (2019) study.

inverse relationship disappeared once they controlled for unobserved land quality. The authors found that farm output was proportional to farm size.

Other authors propose a U-shaped relationship between farm-size and productivity. For instance, Muyanga and Jayne (2019), using a representative sample of farms in Kenya's high-potential zones, found that the relationship between farm size and productivity is: (i) negative on farms between zero and 3 hectares, (ii) relatively at on farms between 3 and 5 hectares, and (iii) strongly positive on farms between 5 and 70 hectares. Other studies have shown that the relationship between land size and productivity depends on the country and region of smallholders and the crop/livestock activities. The choice of the output variables (net returns, gross revenue, yield, total factor productivity, etc.) is used in the analysis (Garzon Delvaux et al., 2020). For instance, Rada and Fuglie (2019) have found, based on a set of case studies, that the size-productivity relationship evolves with the level of economic development of the country. In particular, small farms in low-income or developing countries face relative productivity advantages (an inverse farm size-productivity relationship). In contrast, large farms in developed countries tend to be more productive than small farms. The above literature reveals that there is still no consensus on the relationship between land size (plot size/farm size) and productivity, at least in developing countries.

Recently, there has been growing interest in finding the reasons for land-size IR. Recent research by Otsuka et al. (2016) concludes that owing to technology, IR may disappear in Asian countries. The authors argue that due to the rapid economic growth and wage increases in Asia, labor-saving and machine-using production methods have increased farming efficiency. Large-scale mechanized farms have become more efficient, which tends to weaken the farm-size IR relationship. This is consistent with Deolalikar (1981) work, which found, using cross-sectional regional data from India, that the introduction of technology on traditional farms diminished the IR and reversed so that large farms had higher productivity compared to small farms. However, this reversal of the inverse relationship was explained by the increased importance of credit-intensive cash inputs such as fertilizer and improved seeds that were not necessarily accessible to small farms. The author concluded that the relaxation of credit constraints on small farms could result in the adoption of new technologies, and the IR would disappear or cease to exist. Similarly, Gautam and Ahmed (2019) have found, using total factor productivity (TFP), that the inverse farm size-productivity relationship has diminished over time in Bangladesh due to the development of modern technologies and wage growth. In addition to technology access, several other explanations offered so far in the literature support the IR hypothesis. These include market imperfections, measurement errors, land quality, and farmers' education and skills. Below we discuss the literature in detail.

Market imperfections and IR

In the 20th century, attempts to explain the IR primarily relied on market imperfections that prevented efficient land allocation, including missing land, credit, labor, or insurance markets. Missing land is referred to as land the operator did not realize belonged to him. In a study, Sen (1966) investigated peasant agriculture in India, and his "dual market theory" was the first to show the labor market imperfection. The author found a substantial gap between (the highest) wage rates outside the peasant economy and the (lowest) real wages/cost of labor on the farms. Sen argues that the labor market in the farming sector is characterized by surplus labor and the wage gap,[3] yet small farms will be more productive than large farms in the long run. Using national plot-level data, Ali and Deininger (2015) found that the inverse relationship between farm size and output per hectare existed because of labor market imperfections. Specifically, the authors found that the inverse relationship exists if profits with family labor valued at shadow wages[4] are used but disappear if family labor is valued at the village-level market wage rates. Kagin et al. (2015), using panel data from Mexico found that agricultural wage rates, in particular, tend to be higher on large farms than on small farms. In a comprehensive study, Feder (1985) pointed out that IR relates to the coexistence of imperfections in the land, labor, and capital markets. Also, Barrett (1996) argued that the absence of the insurance market suffices to explain farm-size IR if some small farmers are price-risk averse. Missing markets have been found to explain farm productivity discrepancies between households (see Feder, 1985; Carter and Wiebe, 1990; Kimhi, 2006). Other studies in the literature focus on the supervision cost of hired labor on farms as the IR's likely explanation (see Binswanger et al., 1995; Heltberg, 1998; Deininger et al., 2018). In the early 2000s, Assunção and Ghatak (2003) theoretically showed that farm-size productivity IR results from imperfections in the credits markets and heterogeneity in farmer skills, even after controlling for diminishing returns to any input.

However, imperfect market theories are rejected by Assunção and Braido (2007), who test them using plot-level data from India. They found that smaller plots are more productive than larger ones, even within a farm household. The IR relationship is related to the plot's unobserved characteristics rather than the household. In other words, missing markets cannot explain differences in the productivity of parcels held by the same family. The data shows that the inverse relationship still holds even after controlling for family-fixed effects and household-period fixed effects. With a doubling of plot size, output decreased from 30 to 16% after controlling for observed plot attributes (plot distance to dwelling, plot slope, potential wetness index, and plot title ownership). In conclusion, the characteristics of the farm or the plot influenced the inverse relationship more than the household's characteristics.

Soil quality and IR

Evidence arguing that the IR is a spurious result caused by the omission of soil quality in regression is diverse. For example, Bhalla and Roy (1988) found that soil factors are important determinants of farms' productivity, and the inclusion of soil quality in production

3 Wage gap can exist because of seasonality in production agriculture and institutionally determined minimum wage rate. In harvesting time wage rate is higher than wages in slack time (transplanting of rice). Sen (1966) argues that wage gap in the case of India suffers from market distortions and peasant farming has some distinct advantages (monitoring costs, hiring time, etc.) in the allocation of labor.

4 In this study both hired labor wages rates and opportunity cost of labor in off-farm labor markets were used.

functions could weaken the IR. However, Heltberg (1998) argues that the results obtained by Bhalla and Roy are only valid district-level aggregate data rather than household-level data. Other studies (see Benjamin, 1995; Benjamin and Brandt, 2002; Chen et al., 2011; Larson et al., 2013) have shown that farm-size-productivity IR can be explained by soil fertility (or soil quality)—small farms have more fertile soil than large farms. Lamb (2003) argues that land quality's inclusion largely explains the IR between farm size and profits. In a study of farms in India, Assunção and Braido (2007) found that the IR is related to land value and other plot attributes (namely, soil type and presence of irrigation) rather than the household. In contrast, using Madagascar's data, Barrett et al. (2010) estimated production and yield functions incorporating detailed soil quality measurements. The authors argue that IR can only marginally be attributed to variations in soil quality. A drawback of most of the above studies in developing countries is that they lack precise data on farm-specific soil quality (e.g., soil nutrients).

Measurement errors and IR

Several studies have investigated if IR arises due to statistical and econometric modeling issues stemming from missing data or measurement errors (see Benjamin, 1995; Binswanger et al., 1995; Desiere and Jolliffe, 2018; Abay et al., 2019; Gourlay et al., 2019). Measurement error for land size may explain part of the IR. For instance, in the early 2000s, Lamb (2003) empirically tested the robustness of IR and found that the IR is much stronger in fixed effects than in random-effects estimates. Lamb (2003) finding is consistent with the well-known tendency of fixed effects to exacerbate measurement errors. Similarly, Barrett et al. (2010) estimated production and yield functions that included household-level fixed impacts. They found that only a small portion of the IR is explained by market imperfections, while the possibility of measurement error causes most of the IR. With the application of GPS devices, Kelly et al. (1995) identified that using the GPS method contributes to making land area measurement less costly and time-consuming. In contrast, Carletto et al. (2013) rejected the hypothesis that IR may be a statistical artifact linked to land measurement errors. They found that the IR hypothesis's empirical validity is strengthened by applying better measures of land size—collected using GPS devices in Uganda. Finally, in India, using profits as a measure of output has either weakened the relationship (see Rosenzweig and Binswanger, 1993) or made it disappear completely, as indicated by Carter (1984) and Lamb (2003).

Similarly, Desiere and Jolliffe (2018) consider the measurement error in self-reported production using a new explanation for the relationship between plot size and productivity. They found no IR between plot size and productivity when crop cuts are used to measure output. In contrast, when self-reports of production are used, there is a strong IR. Their findings reveal that when farmers report production, it is over-reported on small plots and underreported on larger parcels and measurement error drives the inverse relationship. The authors conclude that IR is an artifact of systematic over-reporting production on small plots and under-reporting on larger plots. Similar results are obtained by Dillon et al. (2019), who indicate that using three land measurement methods (farmer estimated, GPS, and compass-and-rope), self-reported measurement bias leads to overreporting for small plots and underreporting for large plots. On the contrary, Bevis and Barrett (2020) claim that the edge effect,[5] not the measurement error in self-reports, is the driving explanation for the plot-size IR. They show that the IR for maize in Uganda disappears when controlling for plot perimeter relative to plot size.

Farmer education, skills, and IR

The literature on farmer education and farm efficiency indicates that better-educated and skilled farmers are more productive, and farming skills are developed through farming experience (see Lockheed et al., 1980). Carter (1984) found that if farming skills could be enhanced by credit, it would have a differentiation effect absent an equal distribution. In 2003, Assunção and Ghatak (2003) proved that heterogeneity concerning farming skills could provide another reason for the IR even without diminishing returns. The authors argue that there is a range in which small farms are profitable for skilled peasants and non-profitable for unskilled peasants, leading to an IR between farm size and productivity. High-skilled peasants end up farming small farms because smallholders have higher opportunity costs to becoming wage workers.[6]

However, Assunção and Braido (2007) empirically tested the IR using farm-level data and household fixed-effects from India. The authors found that cross-household heterogeneity (including household size, number of adults, etc.) is insufficient to explain the IR between farm size and productivity. Similarly, Lipton (2010) used differential in farmers' skills as an explanatory variable of farms' productivity, but the evidence does not support that skills could explain the farm-size IR. In a recent study, Henderson (2014) found that household heads with higher education levels tend to be significantly more allocative inefficient; the explanation is beyond the current study's scope. Our review reveals conflicting evidence regarding the relationship among farmers' education, skills, and IR, indicating a theoretical ambiguity.

In summary, from this literature survey, it appears, on the one hand, that there is no clear consensus on the IR hypothesis and, on the other hand, that most of the empirical evidence comes from studies in South and Southeast Asian countries. Pieces of evidence from African case studies remain relatively scarce. Hence, this study aims to contribute to this literature by revisiting the IR hypothesis in Ethiopia, an SSA country, using plot-level and household-level data from the three waves of the Ethiopia Socioeconomic Survey.

Empirical framework

Specification of the models and variables

We use a simple model to test the relation between farm (plot) size and measure of productivity:

$$Y_i = \beta_0 + \beta_1 L_i + \mu_i \tag{1}$$

5 The edge effect refers to the observation that yields at the outer bounds could be higher than yields in the interior of a plot due to the fact that crops along the edges might face less competition for nutrients, water, space and sunlight than crops in the plot's interior.

6 In other words, farmer self-selection into farming could generate IR.

where i denotes the farm (plot); Y is the measure of productivity. L denotes farm (plot) size; μ is i.i.d. error term. β_1 is the parameter of interest for our discussion on inverse relationship, while the β_0 is a vector of intercepts. As explained above, we use two measures of productivity *(Y)* depending on the scale of analysis (plot vs. farm-level). We use yield—self-reported and crop-cut, similar to other studies (Desiere and Jolliffe, 2018; Gourlay et al., 2019)—when we analyze plot size and productivity relationships. However, when we investigate the relationship between farm-size and productivity, we use the value of sales or gross revenue (birr per hectare).[7]

Taking the double-log (natural log) formulation in Equation (1) results in the following specification: $\ln Y_i = \beta_0 + \beta_1 \ln L_i + \varepsilon_i$ where $\ln Y$ is the natural log of Y, β_1 is the elasticity of productivity with respect to land, and ε is i.i.d. error term. Note that this specification will exclude any observation where Y is not positive. However, the farm (plot) distribution remains more or less the same, and our subsequent analysis will be carried out by extending the double-log formulation.

Recall that Equations (1) is ungenerous specifications involving only one independent variable (regressor) and enable us to test the correlation between returns to cultivation and landholding by testing for rejection of the null hypothesis of no relationship, as against the alternative hypothesis of a negative or a positive relationship. However, our estimates are likely to suffer from the problem of omitted variables bias. We estimate less restrictive models by controlling for some theoretically motivated regressors, which are available in our dataset to address this. These fuller specifications can be presented as:

$$\ln Y_i = \beta_0 + \beta_3 \ln L_i + \phi_3 X_{Ci} + \xi_i \qquad (2)$$

where the parameter ϕ_3 explains the association between productivity and a vector of plot and household-specific controls X_C, while ξ is an i.i.d. error term. Some of the farm and farmer-related characteristics, which could have a bearing on the agricultural outcomes that we control, are the extent of irrigation, employment of family labor in cultivation, household assets, number of plots, and age of household head. We can also control for land quality (or plot quality). We use the Ordinary Least Square regression approach to estimate Equation (2). However, OLS only factors in the conditional mean effects of the response variables. Unlike OLS, the quantile regression (QR) approach estimates for the potential scale shift and allows the analyst to drop the assumption that variables operate the same at the upper and lower tails of the distribution as at the conditional mean. QR provides much more information about the conditional distribution of a response variable. Therefore, this study will use the QR approach to understand the IR between farm size and productivity.

7 Gross revenue is the total revenue from agricultural activities, including sales and self-consumption. The LSMS survey does not collect data on the value of consumed production (i.e., farmers cannot recall the value of self-consumed products). They are calculated using self-consumed quantities and local prices inferred from quantities and values of sales. When using gross revenue as a measure of productivity, we replace plot-size by farm size in the regression function.

A quantile methodology: Measuring heterogeneous effects

Quantile regression is an econometric framework that can allow for different relationships between the dependent variable of interest (regressand) and independent variables (or regressors) to varying points of the regressand's conditional distribution. Explicitly, according to Koenker and Bassett (1978), quantile regression generalized the sample quantiles of conditional quantiles expressed in linear functions of explanatory variables. By allowing conditional functions to be specified at any point across the selected quantiles, quantile regression helps describe the whole conditional distribution of the responsive variables with given regressors. Another attribute of quantile regression is its ability to characterize the entire conditional distribution when there is a heteroskedasticity error in the data. According to Variyam et al. (2002), when there is homoskedasticity in the data, the set of slope parameters of conditional quantile functions in the selected quantiles of the responsive variable's distribution is the same as each quantile and with the slope parameters of the conditional mean function. Therefore, the quantile regression across the selected quantiles of the responsive variable's distribution reproduces the OLS slope coefficients with differences in the intercepts.

Quantile regression (Koenker and Bassett, 1978; Buchinsky, 1998, 2001; Koenker and Hallock, 2001) involves the minimization of

$$\frac{1}{n}\left\{\sum_{i:\,y_i \geq \beta' x_i} q|y_i - \beta' x_i| + \sum_{i:\,y_i < \beta' x_i} (1-q)|y_i - \beta' x_i|\right\} \qquad (3)$$

where q is the specified quantile, and n is the sample size. In other words, quantile regression involves the minimization of the residuals' weighted absolute values and uses the maximum information available. In short, the quantile regression method allows an investigator to differentiate the contribution of regressors and the distribution of the dependent variable. Quantile regression has become a core research topic in econometrics due to its advantages over the OLS regression model. There are several advantages to using a quantile regression approach. First, it provides a more detailed conditional distribution of a dependent variable, given a bundle of independent variables. Different quantile coefficients can demonstrate status-dependent impacts, given the current data on inputs, socioeconomic attributes, and soil characteristics. Second, the estimated coefficients from quantile regression are more robust to outliers, as equation (3) intends to minimize the weighted sum of absolute deviations. The truncation problem is also avoided since quantile regression uses the entire sample, eliminating biased estimates when OLS is applied to sub-samples (Heckman, 1979). This study also uses a quantile regression model to measure the various impacts of inputs (fertilizer family, hired, and exchange labor), soil attributes, operator, family, household characteristics, and the actual yield and gross revenue distribution for farms in Ethiopia.

Data and descriptive statistics

We use data from the three waves of the Ethiopia Socioeconomic Survey (ESS), which is nationally representative of farm-households in Ethiopia but is obviously lacking information on large-scale farms.[8] The survey, an ongoing project, collected information on both household wellbeing and agricultural activities in Ethiopia. The survey is a joint project between the Central Statistical Agency of Ethiopia (CSAE) and the World Bank's Living Standards Measurement Survey (LSMS)-Integrated Survey on Agriculture. The World Bank has a tradition of collecting household survey data in many other developing and emerging economies. In the case of Ethiopia, the first wave of the survey was administered in 2011–2012 that included 3,969 rural households, the second wave in 2013–2014 included 5,262 households, and the third wave, 2015–16 included 3,271 households. In this study, we only include households interviewed in all three waves, which are all rural.[9] The survey gathered information on household characteristics, consumption, living conditions, and health. The survey focused on agriculture to collect detailed and accurate agricultural data at the plot level. Households were visited three times during the agricultural year. The first visit, in September–October, collected data on planting activities. Additionally, during this visit, the area of most plots was measured with GPS. The second visit, in November, implemented the livestock module. The final visit, between January and April, collected data on agricultural production and household information. Finally, it should be noted that the first and last visits included detailed information on labor inputs at the plot level, which we also use in our analysis.

Table 1 describes the variables and summary statistics of variables at the plot level used in this study. Columns 2 and 3 of Table 1 report yield and attributes of plots selected for crop cutting and those self-reported by farmers, while column 4 indicates statistical differences across columns 2 and 3. Table 1 reveals that self-reported yield[10] estimates are significantly higher than those based on crop cuts. On the other hand, Table 1 shows that farmers under-report plot size. Additionally, given that crop cuts were conducted on a limited number of randomly selected plots, the number of plots reported by farmers is higher than those selected for crop cutting. Moreover, farmers have varying plot attributes, and differences appear when explaining plot attributes. This is particularly true of the plot elevations where Table 1 indicates a significant difference between the farmer and crop cutting's plot elevation.

Regarding input application, Table 1 shows that a small percentage of fields are irrigated (only 2–4%), a higher share of plots is mono-cropped (i.e., less diversified), and only 10% of the farms applied compost. Still, a higher share of plots used manure. Farmers systematically overestimated the application of commercial fertilizer. Finally, Table 1 shows significant differences in labor usage on the plots. Interestingly, farmers tend to overestimate the family labor usage and underestimate the utilization of hired labor and exchange labor for planting and harvesting seasons (see columns 2 and 3 of Table 1).

8 All data and relevant documentation are available at: go.worldbank.org/HWKE6FXHJ0. This includes a manual detailing the crop-cutting procedures the enumerators followed.

9 The number of households with self-reported measure by waves includes: 1,496 from 2011–12; 2,961 form 2013–14; 2,882 from 2015–16. The number of households where the crop cutting information was collected includes: 1,285 from 2011–12; 1,680 form 2013–14; 1,803 from 2015–16.

10 For aggregation purpose, yields (production per hectare) are converted to monetary values using local prices.

Table 2 describes the variables and summary statistics of variables used at the household level in the case where productivity is measured by gross revenue. Unlike Table 1, where the yield can be estimated by crop cutting, in this case, we only report gross revenue as reported by the farmer. Note that all variables related to farm size, plot attributes, and inputs usage are reported as the average of all plot/fields owned/operated by the farming household.

Results and discussion

Whole sample regression results

We explore the IR between productivity and land size at plot and farm (holding) levels. First, we present our plots-level results for both self-reported by the farmer and crop cut, with and without the inclusion of labor inputs (family, hired, and exchange labor). Table 3 reports the estimate of the relationship between plot size and both self-reported and crop-cut yields. In the case of self-reported yield without labor inclusion, yield decreases with an increase in plot size (or field size).[11] Estimates suggest that doubling plot-size decreases yields by about 35%. This finding is consistent with the literature on a negative relationship between plot size and productivity for several SSA countries.

In the case of crop cut yield without the inclusion of labor use, our finding contrasts with many other studies, including the one by Desiere and Jolliffe (2018). The first row of column 6 in Table 3 indicates a positive and significant relationship between plot size and yields. Results show that doubling plot-size increases yield by 12%. These results are consistent with Alexander and Kokic (2005), Kokic et al. (2006), Sheng et al. (2015), and Sheng and Chancellor (2019), who found a positive plot-size productivity relationship. In the panel estimation presented above, we use fixed effects by including the enumeration area. Note that estimates in Table 3 controls for wave (base wave (2011–12), plot attributes (plot slope, elevation, wetness, distance to dwelling, and land title ownership), plot inputs (mono-cropped or diversified, application of fertilizer, manure compost, and irrigation status) and household attributes (age of the operator, female-headed households (HH), assets, and education of HH).

Table 3 also reports parameter estimates when productivity is measured at the farm level using the farmer's self-reported gross revenue (GR). We also control plot attributes, inputs, and household attributes, including the enumeration area and fixed effects. The third row of column 5 in Table 3 reveals that doubling farm size decreases gross revenue by 71%. These estimates are twice as large as those obtained in the previous measure of productivity (yields—see the first row of column 5 in Table 3). Our results are consistent with Carletto et al. (2013), who found IR between GPS-measured farm size and net revenue per acre among rural Uganda households.

The estimates presented till this point exclude labor inputs (family, hired, and exchange labor). Recall that one of the weaknesses of previous studies was the lack of labor data at the plot or field level. To overcome the above criticism, we included labor inputs in our model. We also further delineate the labor usage for planting and harvesting seasons when the demand for labor is high. Estimates reveal that the inclusion of labor use changes the magnitude of the plot size and yield relationship's coefficients but not the sign. The

11 Here we use plot and field interchangeably.

TABLE 1 Summary statistics, self-reported vs. crop cuts, all waves.

Variables	Self-reported (2)	Crop cut (3)	Difference (*t*-statistics) (4)
Yield[a] (birr/m^2)	8.83 (484.34)	3.05 (54.00)	7.25
Plot characteristics			
Plot-size (m^2)	1,317.13 (14,675.10)	1,858.49 (5,409.17)	−607.84***
Plot slope slope (percent)	13.56 (10.99)	13.84 (11.36)	−0.31**
Plot elevation (m)	1,923.69 (482.90)	1,974.56 (479.63)	−56.17***
Plot potential wetness index	12.62 (1.81)	12.60 (1.95)	0.02
Household has land title (No. = 1)	0.46	0.37	0.10***
Distance of plot to dwelling (Km)	1.85 (55.49)	1.53 (34.55)	0.36
Number of plots	20.38 (16.57)	19.33 (11.94)	1.12***
Plot inputs			
Manure applied (No. = 1)	0.38	0.57	−0.21***
Compost applied (No. = 1)	0.90	0.90	0.00
Organic fertilizer (No. = 1)	0.95	0.97	−0.03***
Irrigated plot (No. = 1)	0.96	0.98	−0.03***
Cropping (monocropped = 0)	0.40	0.12	0.32***
Fertilizer applied (Kg/ha)	1,662.87 (40,701.79)	1,159.59 (10,953.57)	583.08***
Labor inputs			
Family labor planting (days/ha)	20.76 (44.49)	17.05 (32.14)	4.18***
Hired labor planting (days/ha)	6.83 (57.06)	8.88 (63.61)	−2.30***
Exchange labor planting (days/ha)	12.01 (62.12)	15.08 (61.39)	−3.44***
Family labor harvesting (days/ha)	17.17 (32.56)	8.41 (16.56)	10.32***
Hired labor harvesting (days/ha)	4.88 (35.56)	4.11 (27.57)	0.90*
Exchange labor harvesting (days/ha)	13.51 (53.78)	14.51 (49.33)	−1.17*
Household characteristics			
Asset index	0.18 (0.09)	0.17 (0.07)	0.00***
Female sex of operator (No. = 1)	0.17	0.14	0.04***
Age of household head (years)	46.58 (14.75)	47.51 (14.56)	−1.01***
Household head can read and write (No. = 1)	0.56	0.57	−0.00
Observations	86,057	12,119	

Fixed effect: Enumerated area. ***, **, *, denote statistical significance at the 1, 5, and 10% level of significance. The t-statistics are based on design-adjusted standard errors corrected for clustering at the enumeration area. Standard errors in parentheses. All standard errors are clustered at the enumeration area. [a]For aggregation purpose, yields (production per hectare) are converted to monetary values using local prices. Source: LSMS-ISA, Living Standards Measurements Study-Integrated Surveys on Agriculture: 2011–12, 2013–14, and 2015–16.

Variables	Self-reported
Gross revenue (birr/m^2)	278.83 (1,499.37)
Plot characteristics	
Mean Plot-size (m^2)	1,125.60 (15,478.33)
Mean plot slope (percent)	13.22 (10.55)
Mean plot elevation (m)	1,891.44 (488.30)
Mean plot potential wetness index	12.63 (1.72)
Household has land title (No. = 1)	0.48
Mean distance of plot to dwelling (Km)	1.76
Mean number of plots	17.00 (14.38)
Plot inputs	
Manure applied (No. = 1)	0.32
Compost applied (No. =1)	0.90
Organic fertilizer applied (No. = 1)	0.95
Irrigated plot (No. = 1)	0.95
Cropping (monocropped = 0)	0.42
Fertilizer applied (Kg/ha)	1,527.32 (48,578.22)
Household characteristics	
Asset index	0.17 (0.09)
Female sex of operator (No. = 1)	0.20
Age of household head (years)	46.13 (14.88)
Household head can read and write (No. = 1)	0.56
Observations	9,764

Standard errors in parentheses. All standard errors are clustered at the enumeration area. Source: LSMS-ISA, Living Standards Measurements Study-Integrated Surveys on Agriculture: 2011–12, 2013–14, and 2015–16.

plot-size IR still holds in the self-reported yield, but the estimates are significantly lower than those without labor controls. As shown in Table 3, with the inclusion of labor inputs (see Table 3, second row of column 5), doubling plot-size decreases yield by 23%, while the decline was by 35% without labor inputs. Part of the reduction in the magnitude of the estimates could be explained by the inclusion of labor (family, hired, and exchange) used in the planting and harvesting seasons.

On the other hand, the estimates obtained in the crop cut yield regression are slightly higher than those obtained from regressions that exclude labor usage. As shown in Table 3, in the second row of column 6, doubling the plot-size increases yield by 18%. Findings here underscore the notion that estimates are sensitive to the inclusion of labor inputs. Our estimate is slightly lower (about 3% lower) than those obtained by Desiere and Jolliffe (2018). Let us turn our attention to the estimates of IR between farm size and gross revenue per hectare, self-reported by the operator when labor usage is included. In this case, results show a negative and statistically significant relationship between farm size and productivity. The coefficients reported in the fourth row of column 5 in Table 3 show that doubling farm-size decreases gross revenues per hectare by about 87%. Again, these findings underscore the importance of including labor usage (family, hired, and exchange labor) when assessing farm size and productivity relationships.

We further analyzed the impact of farm size on labor input. In particular, we examined the effect of farm size on total labor input (family and hired labor and individually for family and hired labor input. Appendix Table A5 reports regression by labor inputs (total, family, and hired) by planting and harvesting season. Estimates show a strong inverse relationship between farm size and total labor for planting and harvesting seasons. For example, doubling farm size decreases total labor days by about 31% in the planting season and by 18% in the harvesting season. On the other hand, family labor is negatively affected by farm size for both planting and harvesting seasons. Findings reveal that increased farm size could reduce the demand for family labor. Perhaps, any increase in farm size increases the opportunity cost of family labor. Our finding is consistent with Larson et al. (2013), Ali and Deininger (2015), and Desiere and Jolliffe (2018).

Quantile regression results

Table 4 reports the plot size and productivity relationship findings by selected quantiles[12] for both self-reported by the farmer and crop-cut. Parameter estimates reveal an increasing (in absolute terms) effect of plot size on yields in the case of self-reported yield. The magnitude of the coefficient increases (in absolute terms) monotonically with the quantile (see Table 4). For instance, doubling plot-size decreases yields by 29, 36, 42, and 44% for farms in the 20th, 50th, 80th, and 90th quantiles, respectively. Although the relationships between plot size and productivity are negative for all farms, results imply that increasing farm size will have a lower impact on farms' productivity (below the 50th quantile). Interestingly, the 50th quantile (median) estimates are about the same as those obtained in the whole sample regression (see Table 3, the first row of column 5). From the above results, one can conclude that small farms are more efficient regarding the farm-size productivity debate. We observe significant heterogeneity in the farm size and productivity debate.

Table 4 also reports estimates of the model based on crop cut yield. Table 4 indicates a positive and significant effect of plot size on yields. The parameters are statistically significant at the 1% level of significance for all selected quantiles. However, the magnitude of the IR declines with farm size. The magnitude of the coefficient decreases monotonically with quantiles. Estimates show that doubling plot-size increases yields by 15% for farms in the 20th quantile but only 7% for a farm in the 90th quantile. However, the relationship between plot size and yields is insignificant for farms in the 90th quantile. Finally, the 50th (median) quantile estimates are about the same as those obtained from the whole sample regression (see Table 3, the first row of column 6). The above findings show that an additional plot unit (or acreage) would impact farms' productivity at the lower quantiles. Farms in the 70th and higher quantiles have smaller gains from farm expansion and farms in the 90th quantile may not observe any significant benefits from growth.

Table 4 also reports the estimate of farm size and productivity (measured by gross revenue) by selected quantiles. The median

12 Due to space and brevity we only report selected quantiles. Full results for all quantiles is available from authors upon request.

TABLE 3 Whole sample regression summary results.

	Productivity measurement	Variables		Self-reported (5)	Crop cut (6)
Plot-level analysis	Yield (log)	Plot-size (log, m^2)	Without labor inclusion	−0.350***	0.119***
			With labor inclusion	−0.233***	0.175***
Farm-level analysis	Gross revenue (log)	Farm-size (log, m^2)	Without labor inclusion	−0.714***	
			With labor inclusion	−0.873***	

Fixed effect: Enumerated area. *** denote statistical significance at the 1% level of significance. Full results are reported in Appendix Tables A1–A4.

quantile (50th) estimate is similar to the estimates obtained for the whole sample regression (see Table 3, the third row of column 5). The magnitude of coefficients decreases (in absolute terms) monotonically with quantile. However, we find a significant variation in the estimates by quantiles. The estimates tend to decline (in absolute terms) with increasing quantiles. For example, doubling farm size decreases gross revenues by 78% for farms in the 20th quantile and 73% for farms in the 90th quantile.

Appendix Table A8 reports the findings of plot size and productivity (self-reported yield) relationship with the inclusion of labor usage (family, hired, and exchange) for planting and harvesting seasons. Appendix Table A8 shows two general trends. First, the estimates of plot size on yields are smaller than the estimates obtained from the regression model that excluded labor usage. Second, the parameter estimates increase (in absolute terms) with increasing quantiles. For instance, doubling plot-size decreases yields by about 19, 29, and 34% for farms in the 20th, 70th, and 90th quantiles. However, the median impact (50th quantile) of doubling plot size on yields is smaller (a decrease of 25%) compared to estimates from a regression model that excluded labor usage controls (a reduction of 35%).

The crop cut yields (Appendix Table A9), reveal a similar pattern, as reported earlier in this section. Results show that the estimates of plot size on yields decrease monotonically with increasing quantiles. For example, doubling plot-size increases yields by 19, 15, and 11% for farms in the 20th, 50th, and 80th quantile. The above findings reinforce the importance of additional acreage or plot size for farms in the lower than upper quantiles. Specifically, an additional one-square meter of the plot would have a higher impact (14% or more) on yields of farms in the 50th (median) or lower quantiles but only 9% for farms in the 90th and upper quantiles. The median quantile (50th) estimate is similar to the estimates derived from the whole sample regression without labor control variables.

Appendix Table A10 reveals the quantile estimates of regression with the inclusion of labor usage when gross revenues were used to measure productivity. Recall that total revenue farming, our variable of interest, is reported by the farmer. The estimates in Appendix Table A10 show that: (1) The magnitude of coefficients decreases (in absolute terms) monotonically with increasing quantile; (2) the estimates are slightly lower (in absolute terms) compared to the estimates obtained from a regression that excluded labor usage controls. Results in Appendix Table A10 show that doubling farm size decreases gross revenues by about 77 and 75% for farms in the 20th and 90th quantiles.

Tables 5, 6 report the effects of farm size on labor input by selected quantiles. Table 5 shows labor usage in planting seasons. Like previous analysis, we investigate the impact of farm size on the total, family, and hired labor. The result shows that the median (50th quantile) estimates are close to the whole sample estimates. For instance, doubling farm size decreases total labor days by about 30%. Interestingly, we do not find any significant effect of farm size on family and hired labor in all quantiles. However, in the 80th quantile, the farm-size coefficient is negative and statistically significant at the 5% level.

Lastly, Table 6 shows labor usage in harvesting seasons. Results in Table 6 show that only total labor days are significantly affected by plot size Additionally, the magnitude of the coefficient increases (in absolute terms) monotonically with increasing quantiles. In particular, doubling plot-size decreases total labor days by 8% for farms in the 20th quantile and by 32% for farms in the upper quantile (90th). Findings here enforce the view that with increased farm size (plot size in our case), small farms are likely to replace family labor at a lower rate than larger farms (farms in the higher quantile). It also seems that small farms (a farm in the lower quantiles) hire fewer workers compared to large farms (farms in the upper quantiles).

Conclusion and policy implications

The type of farm-household that best fosters economic and social development is a question that specialists and policymakers have debated intensely, at least since the beginning of the 21st Century. Notably, smaller farms mainly use family labor vs. larger ones that use primarily hired workers. The inverse relationship (IR) between farm size and productivity in developing countries has recently garnered considerable attention from applied economists. Much of the empirical evidence for the IR hypothesis comes from South and Southeast Asian studies. However, the IR debate is still somewhat unsettled in Africa, especially in countries in the SSA. Ethiopia, an SSA country, has been facing several complicated issues, including the dominance of small farms, low levels of efficiency, food insecurity, low incomes, and land insecurity through several land policy reforms. Policymakers are interested in designing policies to consolidate small and large farms to increase farmers' productivity, efficiency, and income. Hence, the objective of this study was to examine the IR hypothesis and investigate whether (or not) land consolidation is a suitable policy to increase agricultural productivity in Ethiopia. The study used plot-level and household-level data from farming households' data and panel analysis.

We used three waves of LSMS data (2010–11, 2012–13, and 2015–16) from the World Bank and the Central Statistical Agency of Ethiopia. This dataset is nationally representative of farm-households in Ethiopia but lacks information on large-scale commercial farms. However, this is not a major drawback given the low contribution of commercial farms on Ethiopia's overall agricultural land use and production and their modest economic spillover effects on neighboring smallholders in terms of job creation, technology and access to inputs (Ali et al., 2017).

To the best of our knowledge, the present study is unique for several reasons. First, we investigated the relationship between productivity and land size at both plot and farm (holding) levels (previous studies focused on one level, either plot or farm size, not both) using two different productivity measures: yield and gross revenue. Secondly, we used self-reported (farm operator) and crop-cut yields to tease any biases in reporting and mismeasurement. Third, we systematically included control variables (plot attributes, plot inputs, household and operator attributes, and labor inputs). Finally, we repeat the above exercise using the quantile regressions (QR) approach. The QR approach helped us to assess heterogeneity in the IR hypothesis. Yet, the QR approach enabled us to determine the IR hypothesis for small farms (those at the lower quantiles) and large farms (those at the higher quantiles).

Findings from this study reveal several interesting patterns. First, consistent with previous literature, farmers tend to over-report their yield and gross revenues. Results strengthen the mismeasurement argument (by farmers for both yield and revenues). We find a negative and significant relationship between plot size, self-reported yield, and gross revenue. However, the impact on gross revenue is larger than those obtained in yields. Recall exact gross revenues could be affected by measurement problems and rounding error problems. Second, in the case of crop cut yields, we find a positive and statistically significant effect of plot size on productivity. Third, when we include labor inputs in the model, we found that plot size's impact on productivity is significantly reduced in self-reported yields and gross revenue. In the crop cut yield, we discovered that the plot-size coefficient's magnitude increases but is still positive and significant. The above findings strengthen the argument of misspecified models. Fourth, we found that total labor input decreases with increased farm size. This is true for total labor inputs, regardless of planting or harvesting seasons. A possible explanation may include that farmers may use more machines which would have implications for large farms. Increasing farm sizes significantly reduces family labor input. This finding suggests that with an increase in farm size, family labor is better suited elsewhere. Perhaps hired labor is more efficient and educated to undertake production on larger farms.

Findings from the quantile regression underscore the importance of heterogeneity in the IR hypothesis. In the case of self-reported yield, we find a strong IR relationship between farm size and productivity; the magnitude of the effect increases (in absolute terms) monotonically with quantile. In the case of crop cut yields, estimates reveal a strong positive effect of farm size on productivity and the magnitude of the IR effect decreases monotonically with quantile. In the case of gross revenue, we found that farm-size displays a robust negative effect on gross revenue, and the magnitude of the effect increases (in absolute terms) monotonically with quantile. The other findings were: (i) the effect of farm size on productivity decreases in magnitude when we control for labor input; (ii) the IR between farm size and total and family labor was significantly negative and the effect increases (in absolute terms) monotonically with increasing quantiles. This finding has implications for total and family labor. Family labor is more important to small farms in both seasons but more so in the planting season. Perhaps the opportunity cost of family labor is higher in the non-farm sector.

TABLE 4 Quantile regression summary results.

	Productivity measurement	Variables		Selected quantiles					
				20	40	50	70	80	90
Plot-level analysis	Yield (log)	Plot-size (log, m^2)	Self-reported	−0.290***	−0.337***	−0.356***	−0.396***	−0.416***	−0.444***
			Crop cut	0.153***	0.127***	0.116***	0.094***	0.084***	0.072**
Farm-level analysis	Gross revenue (log)	Farm-size (log, m^2)	Self-reported	−0.778***	−0.764***	−0.757***	−0.744***	−0.738***	−0.729***

Fixed effect: Enumerated area. ***, **, denote statistical significance at the 1 and 5% level of significance. Full results are reported in Appendix Tables A6, A7.

Variables	Total labor selected quantiles					
	20	40	50	70	80	90
Plot-size (m^2)	−0.081 (0.023)***	−0.144 (0.017)***	−0.176 (0.016)***	−0.242 (0.020)***	−0.278 (0.024)***	−0.323 (0.030)***
Observations	9,277	9,277	9,277	9,277	9,277	9,277
	Family labor selected quantiles					
	20	40	50	70	80	90
Plot-size (m^2)	−2.157 (12.731)	−3.807 (12.534)	−4.633 (19.893)	−7.346 (48.079)	−9.796 (74.388)	−15.274 (133.641)
Observations	9,277	9,277	9,277	9,277	9,277	9,277
	Hired labor selected quantiles					
	20	40	50	70	80	90
Plot-size (m^2)	0.644 (6.714)	0.356 (6.368)	0.215 (6.279)	−0.402 (6.563)	−1.229 (8.348)	−3.863 (17.905)
Observations	9,277	9,277	9,277	9,277	9,277	9,277

Dependent variable: Labor usage (days/ha). Fixed effect: Enumerated area. ***, denote statistical significance at the 1% level of significance. All specification control for plot, plot input, operator and household attributes. Base wave 2011–2012. All standard errors are clustered at the enumeration area.

Findings from this study contribute to a larger body of literature questioning the IR between farm size and productivity. The present study underscores the problems of errors in self-reporting or refusal in survey data and may be contributing to the IR. The study also confirms previous studies conducted in Ethiopia and elsewhere, showing that IR is driven by measurement errors caused by self-reporting or/and misperceptions. Lamb (2003) was the first to suggest, using data collected on rural households in three distinct agro-climatic regions of India, that measurement error in the self-reported land area could explain the inverse farm and plot-size relationship. More recently, Gourlay et al. (2019) found, based on a two-round household panel in a district of Eastern Uganda, that IR holds when using conventional, farmer-recalled crop yield measures. Still, the relationship disappears when yields are measured *via* crop cutting. Similar results are obtained by Desiere and Jolliffe (2018) and Abay et al. (2019) in the context of Ethiopia when comparing farmer-recalled yield and yields derived from crop cuts. Finally, Gollin and Udry (2021) found, using rich panel data from farms in Tanzania and Uganda, measurement error and heterogeneity together account for a significant fraction of the dispersion in measured productivity.

However, it is essential to recall that although the crop cut method is considered the gold standard for yield estimation, it is not free from errors. For example, because the crop cut estimates yields are obtained from a sampling of small subplots within cultivated plots, there is a greater risk of sampling error if yields within the plot are heterogeneous (Desiere and Jolliffe, 2018). Another example is the crop-cut method measures the biological yield, which does not necessarily consider harvest losses and therefore does not reflect the economic yield that is of use to the farmer or planner (FAO, 2017). Given that all sources of upward bias reported for crop cuts can be eliminated when the entire field is harvested, whole plot yield reporting (also called whole plot harvesting) could be a better alternative to crop-cut and self-reporting methods. Nevertheless, the method is also costly, time-consuming and unsuitable for large sample sizes or multiple crop studies (see Fermont and Benson, 2011; FAO, 2017 for a review of different methods for crop yield estimation).

From a policy perspective, this study highlights the role that policymakers might play in slowing down (or refocusing) the debate on IR by (i) removing, or at least reducing, measurement error in both yields, which affect both crop-cut and self-reported yield, (ii) standardizing measurement units and tools for land, and (iii) reducing imperfections in the land, labor and credit markets. The government should also consider undertaking an extensive collection of farm and household-level data to understand better the influence of plot and farm-household characteristics on IR. For instance, surveys need to collect information on cropping practices, soil conditions, the value of self-consumed products, labor inputs (family, hired, and exchange labor), operator and household attributes, seasonal demand, and labor supply across and within the farming household.

Secondly, this study reveals that land consolidation is not always beneficial and may lead to unfavorable effects, mainly for less efficient/productive farms. Policymakers may gain from being cognizant of heterogeneity in farms and that one policy may not fit all farms. A signal strand of policy can address the issue of increased food security and livelihood by farm consolidation. A concentrated effort to implement land consolidation should, therefore, preferably be combined with other instruments to increase its impact. Finally, policymakers need to provide greater support to small farms or facilitate their access to off-farm job opportunities.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found below: https://www.worldbank.org/en/programs/lsms.

Author contributions

Conceptualization and writing—original draft preparation: AM. Statistical data analysis methodology and investigation: AM and KL. Writing—review and editing, supervision, and project administration: GG, SGP, and KL. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

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Adoption of dairy technologies in smallholder dairy farms in Ethiopia

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The adoption of modern agricultural technologies in Ethiopia's dairy production system remains underutilized and under-researched yet it is a promising sector to aid in reducing poverty, improving the food security situation and the welfare of rural households, and in ensuring environmental sustainability. This paper uses the Negative Binomial regression model to examine determinants of multiple agricultural technology adoption in the Addis Ababa and Oromia regions of Ethiopia. Data was collected from 159 smallholder dairy farms in Ethiopia's Addis Ababa and Oromia regions exploring 19 technologies used by the farmers during the study period. The findings show that farm location and herd size impact adoption decisions. Increasing herd size is associated with increased uptake of multiple technologies. Further, as farmer education level increases the more likely farmers are to adopt multiple technologies. The increase in the number of female workers is positively associated with the adoption of multiple dairy technologies. In terms of farmers'/workers' years of experience, those with no years of work experience are less likely to have adopted multiple technologies than those with more than 5years of experience. However, this could be due to a number of factors where experience stands as a proxy value. Trust in information from government agencies was associated with a higher propensity to adopt multiple dairy technology as was farmer perception of fellow farmers as peers compared to those who perceive them as competitors. This is an important finding as it may help policymakers or institutions explore knowledge exchange and diffusion of innovation strategies tailored to specific farming and community situations. Studies have shown that farmers within a social group learn from each other more fully about the benefits and usage of new technology. These findings are of value in future technology adoption studies, particularly which factors influence the intensity of adoption of multiple technologies by smallscale producers.

KEYWORDS

milk hygiene, animal health, food safety, biosecurity measures/adoption, constraints, dairy technologies, smallholder, Ethiopia

1. Introduction

Globally, livestock production contributes 40% to global agricultural Gross Domestic Product (GDP) and to an estimated 30% of agricultural GDP within the developing world (Abbasi and Nawab, 2021). Dairy production, a sub-sector of livestock production, is important for the livelihood of many smallholder farmers in the developing world (Janssen and Swinnen, 2019; Abbasi and Nawab, 2021). Smallholder dairy production systems in Sub-Saharan African (SSA) countries are characterized by low productivity and a slow rate of technology adoption (Mekonnen et al., 2010). This is equally the case in Ethiopia where adoption of dairy technologies and practices has been slow, despite numerous efforts to disseminate the technologies in the past.

Several factors contribute to this low productivity and slow rate of adoption; among them animal disease, livestock nutrition, poor management, lack of infrastructure, and veterinary service provision (Kebebe, 2017; Tschopp et al., 2021). The adoption of modern dairy technologies such as use of improved breeds, improve forage, promoting animal health and hygiene is important to drive productivity, farmer's profits, welfare of poor farmers and is promising as a driver of rural development and poverty reduction (Janssen and Swinnen, 2019). There is thus a need for policies that increase technology adoption and agricultural productivity which can significantly reduce poverty (Zegeye et al., 2022). To realize significant productivity gains multiple adoption of advanced agricultural technologies and better production practices by small holder farmers should be a priority (Ojango et al., 2017), as a pathway out of poverty and food insecurity (Mekonnen et al., 2010; Kebebe, 2019).

Ethiopia has the largest cattle population in Africa and dairy production is dominated by smallholder farming systems with cattle managed in traditional ways. The cattle have multiple uses such as wealth storage, draft power and milk production (Mekonnen et al., 2010; Chagwiza et al., 2016). Dairy production is an important pillar of the Ethiopian economy creating employment and livelihood opportunities (Mekonnen et al., 2010; Chagwiza et al., 2016). Increasing population, urbanization, and the rise in consumers' incomes are expected to increase the demand for dairy products in Ethiopia (Mekonnen et al., 2010; Chagwiza et al., 2016). Therefore, smallholder dairy production will increasingly become important for the improvement of the livelihoods of poor rural communities while contributing to food security (Mekonnen et al., 2010). The adoption of modern agricultural technologies in smallholder farming is a promising strategy in Ethiopia for improving the welfare of rural households, reducing poverty, improving food security and ensuring environmental sustainability (Zegeye et al., 2022).

Ethiopia has many endemic cattle diseases, some being zoonotic, that can harm smallholder dairy farmers and consumers. Growing consumer awareness of food safety risks, food safety legislation and increasing standards of milk quality being demanded by dairy processors has led smallholder farmers to adopt hygienic milking, milk handling and storage practices, biosecurity and animal health technologies to ensure improved milk quality (Kumar et al., 2016; Burkitbayeva et al., 2019). It is therefore important that farmers adopt multiple technologies including biosecurity, animal health and hygiene technologies and practices that reduce the risk of disease introduction and spread within cattle herds, reducing zoonoses risks and helping to address antibiotics resistance associated with the overuse of veterinary drugs (Sarrazin et al., 2014; Ritter et al., 2016). There is however, a limited number of studies that have investigated the multiple adoption of biosecurity, animal health and hygiene technologies and practices in smallholder dairy farms in Ethiopia. Thus the significance and need for this paper. While extant literature has explored the adoption of technologies in Ethiopia (Mekonnen et al., 2010; Dehinenet et al., 2014; Kebebe et al., 2015; Kebebe, 2017; Kebebe, 2019) they have mostly explored a narrower range of the available technologies for dairy production, with limited studies considering the intensity of multiple adoption. Extant literature suggests that despite increased dissemination efforts (Kebebe, 2017), the adoption rate of technologies in the dairy sector has been slow (Russell and Bewley, 2013; Barrios et al., 2020).

We investigated the adoption of 19 dairy technologies in Addis Ababa and Oromia regions of Ethiopia, concentrating on the importance and the influence of the socio-economic factors described herein as adoption intensity. Measuring adoption intensity requires several assumptions (Rahelizatovo and Gillespie, 2004) such as the adoption of any one of the 19 technologies would not preclude the use of any of the other 18 dairy technologies. However, the implementation of one technology may not be independent of the implementation of another technology, because many of them may be complementary. Also, the use of more dairy technologies may be preferential in terms of productivity gains compared to the adoption of fewer technologies (Rahelizatovo and Gillespie, 2004; Akzar et al., 2019).

Our study differs from more commonly used approaches, which focused on each specific technology; we view adoption in terms of the total number of technologies implemented over a period of time. The study used a count data analysis, the Negative Binomial regression model, similar to that used by Rahelizatovo and Gillespie (2004), Kumar et al. (2020), Nonvide (2021), and Yang et al. (2021) in the analysis of the adoption of technologies in agricultural production. This type of analysis is advantageous in situations where there are large numbers of technologies that might be adopted, and the researcher(s) wish to examine the intensity of technology adoption. Other analyses that have examined the adoption of multiple technologies have used multinomial probit or logit or multivariate probit (see Kebebe, 2017) and a latent class analysis (see Akzar et al., 2019) frameworks. Such models, however, provide significant computational difficulties when the number of technologies being adopted by farmers becomes greater than two, in the case of multinomial logit, or four or five, in the case of multivariate probit. And even more difficult when all the studied farmers were able to adopt more than four or five technologies. The obvious disadvantages of count data analyses compared with other approaches are that they provide little information as to the type of producer who would adopt a specific technology. The advantage of this finding is that it can be useful for policymakers as interventions can be formulated to target the less intensive adopters.

Data was collected from 159 smallholder dairy farms in Ethiopia's Addis Ababa and Oromia regions exploring 19 technologies that could be potentially used by the farmers during the study period. The findings show that farm location and herd size impact adoption decisions. Increasing herd size is associated with increased uptake of multiple technologies. Further, as farmer education level increases the more likely farmers are to adopt additional dairy technologies. The increase in the number of female workers is positively associated with the adoption of multiple dairy technologies. In terms of farmers'/workers' years of experience, those with no years of work experience are less likely to adopt more technologies than those with more years of experience. However, this could be due to a number of factors where experience stands as a proxy value. Trust in information from government agencies was associated with a higher propensity to adopt dairy technologies as was farmer perception of fellow farmers as peers compared to those who perceive them as competitors. This is an important finding as it may help policymakers or institutions explore knowledge exchange and diffusion of innovation strategies tailored to specific farming and community situations. Studies have shown that farmers within a social group learn from each other more fully about the benefits and usage of new technology. These findings are of value in future technology adoption studies, particularly considering the less intensive adopters.

The rest of the paper is organized as follows: section 2 outlines the factors influencing dairy farmers decisions to adopt multiple dairy technologies; section 3 describes the data and methods; section 4 describes and discusses the empirical results; and section concludes the paper.

2. Factors influencing dairy farmers' decisions to adopt multiple dairy technologies

The adoption of dairy technologies by farmers varies widely across different agro-ecologies and within the same agro-ecology based on various technical and non-technical factors (Dehinenet et al., 2014). Researchers have studied numerous motivating factors and constraints to adoption by observing the different behaviors between adopters and non-adopters of technology (Ruzzante et al., 2021). They found that the influence of many factors can be explained by; the level of diffusion of the specific technology, the economic constraints of the adopters and the perception of adopters to the technology (Ruzzante et al., 2021). Technological, economic, institutional, and human specific factors have been found to be key determinants of technological adoption (Mwangi and Kariuki, 2015) coupled with unobserved cultural, contextual, and policy factors (Ruzzante et al., 2021). Some of those factors are family size, farming experience, availability of dairy production extension services, availability of cross breed cows, accessibility of saving institutions, total income from milk and milk products, availability of training on livestock, age of household head and off-farm activity participation played significant roles on both the probability of dairy technology adoption and its level of adoption (Dehinenet et al., 2014). Higher levels of technology adoption are associated with better milk yield regardless of the breed of cattle (local or crossbred) owned by smallholder dairy farmers (Mekonnen et al., 2010). Adoption of new practices and technologies is however limited by various factors such as affordability, and limited access to information and training (Akzar et al., 2019; Janssen and Swinnen, 2019), which is a major constraint to quality, and higher milk yields.

Two properties determine the adoption of agricultural technologies namely the key aspects of decision-making and diffusion theory. The first is the change in the production function. That is, with the same level of inputs, the level of output may increase due to technology adoption. In other words, the same output level can be produced with fewer inputs which can lead to improved efficiency of agricultural production (Nonvide, 2021). The second attribute of the adoption of new agricultural technologies is the increase in profitability. Farmers base their adoption decision on the expected utility. In this case, and in line with neoclassical microeconomic theory, the farmer may decide to adopt a technology when it provides him a utility greater than non-adoption (Nonvide, 2021; Ruzzante et al., 2021). In this case, farmers may be more likely to adopt multiple technologies as being complementary or substitutes for current practice, specifically to maximize their expected benefit from their adoption decisions despite being constrained by their limited budget and access to information (Akzar et al., 2019). In this study, adoption theory is used to contextualize and interpret the causal (or contributory) relationship affecting the number of technologies adopted by farmers in this context.

3. Data and methods

3.1. Description of the study area

This research was undertaken within a bovine tuberculosis control project in the wider Addis Ababa and Oromia milk shade in Ethiopia. The study area comprised urban and peri-urban and intermediate rural areas within a 60 km radius of Addis Ababa, the capital city of Ethiopia. The urban areas consisted of Bole, Kolfe, Ketema and Kaliti sub-cities of Addis Ababa while Sendafa, Sebata, Debre-Zeit, and Holeta made up the peri-urban areas located in the Oromia region. This study area was selected based on several factors. First, dairy production in the area is an important economic activity for dairy farmers (Deneke et al., 2022). The region is undergoing rapid urbanization which creates new dairy production constraints such as reduced land availability and lack of forage due to the loss of grazing areas (Alemayehu et al., 2021; Deneke et al., 2022). The high prevalence of endemic zoonoses is a major public health problem for both farmers and consumers of animal source products (Amenu et al., 2019; Gizaw et al., 2020). Finally, climate change is creating new production challenges for smallholder farmers including heat stress, limited access to feed resources and new pests and diseases (Yengoh and Ardö, 2020).

This study had ethical clearance from ALERT hospital AHRI/ALERT Ethics Review Committee (AAERC) approval (Protocol number PO-(46/14)) and the University College London Research Ethics Committee (UCL-REC) approval number 19867/001.

The questionnaire used to collect the data was based on the identified research gap following a structured literature review on dairy production and technology adoption in the Ethiopian context. The questionnaire covered topics such as farmer socio-economic characteristics, dairy technology adopted and possible drivers and constraints to technology adoption. The dairy technologies explored in this study focused on breed improvement, animal health, biosecurity and feeding technologies. Breed improvement technologies considered included animal purchasing and breed improvement included AI, breed upgrading, and testing new animals (Mekonnen et al., 2010; Burkitbayeva et al., 2019). Biosecurity and hygiene practices and technologies explored in the questionnaire included visits by a veterinarian, presence of biosecurity plans, fencing, disinfection baths, improved housing and use of improved containers meant to prevent diseases being introduced to a farm (Sarrazin et al., 2014; Ritter et al., 2016). Feeding technologies considered included zero grazing, purchase of feeds/forage and growing own feeds/forage which are meant to improve livestock performance (Mekonnen et al., 2010). Animal health technologies explored included ectoparasite control, endoparasite control, animal health records, vaccination, teat disinfection and dry cow therapy which are meant to reduce disease burden and improve animal welfare (Mekonnen et al., 2010; Kumar et al., 2015).

The questionnaire was administered to a total of 159 farmers selected through convenience and purposive sampling methods. The selected farmers had previously participated in the Ethiopia Control of Bovine Tuberculosis Strategies (ETHICOBOTS) project work. The inclusion criteria were willingness to freely participate in the study and experience of around 5 years in farming. In cases where a farmer declined to participate, or the farm had ceased to operate, an alternative farm within the study areas with similar characteristics was selected as a replacement.

3.2. Empirical strategy: the negative binomial regression model

The study investigates the likelihood of a farmer adopting the 19 improved technologies/practices iteratively derived from the extant literature. The methodology determines how many technologies or practices are adopted (multiple adoption) and how the adoption of multiple technologies/practices is affected by different factors. The events of adopting the various dairy technologies were assumed to occur at a constant rate within each farm but were allowed to vary across farms. The events can, therefore, be considered as generated by a Poisson process. The density function associated with the Poisson model is expressed in Equation (1):

$$f\left(y_i|x_i\right) = \frac{e^{-\mu_i}\mu_i^{y_i}}{y_i!} Y; = 0,1,2,\ldots, \quad (1)$$

where x_i are variables that affect the adoption of the technologies. The mean parameter μ; represents the expected number of events and is expressed as in Equation (2):

$$\mu_i = E\left[y_i|x_i\right] = \exp\left(x_i'\beta\right) \quad (2)$$

If we assume the independence of the observations, one can express the log-likelihood function associated with the estimation as in Equation (3):

$$\ln L\left(\beta\right) = \sum_{i=1}^{n}\left[y_i x_i'\beta - \exp\left(x_i'\beta\right) - \ln y_i'!\right] \quad (3)$$

Properties of the Poisson regression model require the mean and variance of v, to be equal. However, the assumption of a constant rate of adoption may not be realistic in practice. The variance of v, can be greater (lower) than its mean value, indicating the presence of over- (under-) dispersion in the count data. In such a case, the Poisson regression would not be fully efficient, and the estimated standard errors would be biased and inconsistent. The negative binomial analysis allows for an adjustment for the presence of overdispersion and permits a flexible modeling of the variance. The variance function for the negative binomial model is presented in Equation (4), in which a is the dispersion parameter to be estimated:

$$\operatorname{var}\left(y_i\right)^n = \mu_i + \alpha\mu_i^2 \quad (4)$$

The Poisson regression is a special case of the negative binomial with $\alpha = 0$. Under the assumption that the specification of the mean is the same as that in the Poisson regression model, the log-likelihood function associated with the negative binomial formulation is expressed in Equation (5):

$$\ln L\left(\alpha,\beta\right) = \sum_{i=1}^{n}\left\{\sum_{j=0}^{y_i-1}\ln\left(j+\alpha^{-1}\right) - \ln\left(y_i!\right) - \left(y_i+\alpha^{-1}\right)\ln[1+\alpha\exp\left(x_i'\beta\right] + y_i\ln\alpha + y_i x_i'\beta\right\} \quad (5)$$

In summary, the Poisson model is not particularly appropriate if the probability of an event is more balanced, which is the case in our study. As the underlying assumption in this study is that all events (adoption of a technology) have the same probability of occurrence is violated as the probability of adopting the first technology could differ from the probability of adopting a second or third practice, given that in the latter case the farmer has already gained some experience with adoption of a given technology, and/or there is an aggregated enhanced benefit of adopting multiple technologies, or having adopted one technology this may limit farmers ability to fund further adoption. Therefore, the number of technologies adopted by farmers is considered as an ordinal variable and therefore a negative binomial (NB) regression analysis was employed, and we obtain similar findings as those of the Poisson. The advantage with NB is that it loosens the restrictive assumption with the Poisson Regression that the variance should be equal to the mean. And hence it is an appropriate estimation strategy for this case.

3.3. Descriptive statistics

The majority of the dairy farmers in this study had adopted several of the 19 technologies (Table 1), namely, breed improvement, purchases of commercial feeds and minerals, vaccinations control of endoparasites (i.e., worms and flukes), fencing, use of AI for breeding, teats disinfections, zero-grazing feeding system, control for ectoparasites (i.e., ticks), keeping of records, having a biosecurity plan, keeping records of cattle deaths that occur in the farm, growing of feeds in the farm, use of disinfection footbath to be used before entering the shed, vet visits, improved housing, containers used for milking and storage, dry cow therapy, and testing new cattle before introducing them to the herd as shown in Table 1.

In the survey, dairy producers were asked which of the 19 dairy technologies and practices they had adopted. Table 2 summarizes each technologies and which have been grouped into four categories: (1) animal purchasing and breed improvement including AI use, breed upgrading, and testing new animals, (2) Biosecurity and hygiene, for example, visits by a veterinarian, farm having a biosecurity plan, fencing, disinfection baths, improved housing and use of improved milking and storage containers, (3) Feeding such as the adoption of zero grading, purchase of feeds, growing own feeds, and (4) Animal health related ectoparasite control, endoparasite control, animal health records, vaccination, teat disinfection and dry cow therapy. The farmers response regarding his or her current adoption of each of the technology was considered as an event. Count numbers of technologies and practices adopted on the farm constituted the dependent variable in the study. Furthermore, the expected number of events E(Y) and the hypothesized independent variables were assumed to have a log-linear relationship, as in Equation (2).

TABLE 1 Summary of the number of technologies adopted and the percentage of adopters.

Number of technologies adopted by dairy farmers (count)	Number of adopters (count)	Adopters in percentage
4	1	0.63
5	1	0.63
6	2	1.26
7	6	3.77
8	18	11.32
9	27	16.98
10	19	11.95
11	24	15.09
12	23	14.47
13	7	4.4
14	11	6.92
15	6	3.77
16	6	3.77
17	3	1.89
18	2	1.26
19	3	1.89
Total	159	100

TABLE 2 Thematic grouping of the dairy technologies explored in this study.

Groups	Description
Animal purchasing and breed improvement	AI use, breed upgrading, and testing new animals
Biosecurity and hygiene	Visits by a veterinarian, farm having a biosecurity plan, fencing, disinfection baths, improved housing and use of improved milking and storage containers
Feeding	Adoption of zero grading, purchase of feeds, growing own feeds
Animal health	Ectoparasite control, endoparasite control, animal health records, vaccination, teat disinfection and dry cow therapy

Table 3 shows the rate of adoption of individual technologies by the farmers in the sample group. They are listed from the most frequently adopted technologies, breed improvement and purchase of commercial feeds and minerals (96%), vaccination (94%), control for endoparasites, i.e., worms and flukes (94%), fencing (91%), using AI for breeding (86%), disinfection of teats (79%), use of zero-grazing (78%), control for ectoparasites, i.e., ticks (76%), and health records (51%) to the least commonly adopted (testing new cattle before introducing to the herd, 14%).

Least adopted technologies were a biosecurity plan (44%), record keeping of cattle mortality on farm (44%), growing feed/forage on farm (30%), disinfection footbath use on entry to cattle sheds (28%), veterinary visits (27%), improved housing (25%), containers used for milking and storage (17%), dry cow therapy (16%), and testing new cattle before introducing them to the herd (14%). This demonstrates that the majority of the farms adopt more animal purchasing and breed improvement related technologies, followed by those for biosecurity and hygiene, then animal feeding, then lastly animal health related biosecurity measures.

In addition, Table 4 provides a correlation matrix showing significance level and the magnitude and direction of the associations for the technologies adopted. Table 4 shows that there is a positive and weak association between breed improvements and records of deaths, health records, and zero grazing, while strong positive correlations were observed for improved housing and biosecurity plan, disease testing, disinfect teats and disinfection using footbaths and a negative moderately strong correlation between improved housing and disinfecting teats. Table 5 shows the means of the key socio-economic variables used in this paper for farmers and their farms, i.e., farm location, herd size, age of farmer, the highest level of education of the farmer, number of male and female workers, years of experience, trust in information from government, government agencies or from other farmers and whether they perceived their fellow farmers as peers or competitors and some institutional variables, such as membership of farmer organizations/groups.

The mean of the technologies adopted were 11.5 (SD = 2.88). The average age of farmers in the study was 41.65 (SD = 21.73), while the average herd size was 16.53 (SD = 17.89), showing that there is a wide dispersion of herd size across the sample population. In terms of the farm locations, farms were sited in the following areas Holeta (21%), Bole (19%), Sebeta (17%), Bishoftu (14%), Sendafa (11%). Kaliti (9%), Ketema and Kolfe (both 4%). With regard to education the sample population with no education was (6%), primary education (31%), secondary education (38%) and tertiary education (25%). The mean of the number of female workers use were 1.31 (SD = 2.60), 68 farms did not exploy any female workers while another farmers had up to 19 female workers showing there is a wide dispersion in the number of female workers across the study farms. The mean for male workers was 3.11 (SD = 5.66), 18 farms did not employ any male workers, while another farmer has 35 male workers on the dairy farm. This show there is a wide dispersion in the number of male workers used on the dairy farms. In terms of years of dairy farming experience, those who had no experience were 23%, 1–5 years (24%), 6–7 years (14%) and more than 10 years (38%). Trust was reported in government information (91%,) government agencies (93%) and other farmers (82%) with the majority of farmers (72%) perceiving fellow farmers as peers. Nearly one quarter of the farmers (23%) were members of farmers organizations/group, while 21% of the dairy farmers had additional income. These variables deduced from the literature review were positioned as being to the adoption of agricultural technologies in Ethiopia.

4. Results

4.1. Factors influencing dairy farmer's adoption of multiple dairy technologies

The results of the Negative Binomial Regression are presented in Table 6 and estimates associated with the marginal effects are computed at the mean values of the Xs. Comparison of the values of the mean and variance of the dependent variable technologies showed

TABLE 3 Rate of individual technologies adoption by farmers.

Technologies	Adopters (percentage of study population)
Breed improvement	96%
Purchased commercial feeds and minerals	96%
Vaccinate	94%
control for endoparasites (i.e., worms and flukes)	94%
Fencing	91%
Using AI for breeding	86%
Disinfect teats	79%
Animals feeding in a zero-grazing	78%
control for ectoparasites (i.e., ticks)	76%
Health records	51%
Biosecurity plan	44%
Record keeping of cattle deaths that occur on the farm	44%
Grow feeds for your cattle on your farm	30%
Use disinfection footbath to step through before entering the cattle shed	28%
Vet visit	27%
Improved housing	25%
Containers used for milking and storage	17%
Dry Cow Therapy	16%
Testing new cattle before introducing them to the herd	14%

a variance (2.88) compared with the mean (11.04). This would suggest the inappropriateness of using the Poisson model, because the equality property of the mean and variance was not fulfilled. Tests for overdispersion indicate that one should consider a variance function-type negative binomial. The Negative Binomial Regression model yielded a log-likelihood value of (−365.28), similar to that of the Poisson. The Poisson was estimated for robustness. The results from the two regressions were very similar.

The results suggested that, for the two regions Oromia and Addis Ababa those dairy producers' having a larger herd size, reside in Kolfe and Sendafa, having no education, employing female workers, having limited experience, trusting in information from government agencies and perceiving fellow farmers as peers were significantly more likely to adopt multiple dairy technologies.

Furthermore, being from Kolfe yielded the greatest marginal effects compared with other explanatory dummy variables. Such results show the importance of efforts to stimulate regional reach in inducing technology adoption. A farmer who is from Kolfe (which is a location in Addis Ababa) is more likely to be willing to adopt technology than those in other regions. While a farmer from Sendafa (which is a location the Oromia region) is more reticent to adopt technology compared to other regions. Both regions are known for their high dairy production sector and have varying agroecological characteristics. The study shows a differing effect on willingness to adopt multiple technologies. This is a valuable finding while exploring interventions for uptake of the dairy technologies, Adoption of technology is not a linear process, it is often dynamic requiring an understanding of the decisions made by individual farm households (Ruzzante et al., 2021). The findings in this study show variations by context, such as farm location, as well as factors such as level of education, herd size and number of female workers. These factors, both individually and in a concerted manner, influence decision-making at the farm level. Further examples of non-linearity are that due to the different risk appetites of farmers some may wish to see the benefits of technology adoption over a longer period of time, or may wish to see other peer farmers experiment before they are willing to engage in the adoption process.

The positive effect of farmers having trust in information from government agencies, such as extension officers, is associated with the adoption of a greater number of dairy technologies. This may suggest that having an institutional trust will stimulate multiple adoptions of technologies. Similarly, the positive effect associated with how they perceive their fellow farmers as 'peers' suggests that farmers who perceived their fellow farmers as peers are more likely to engage in multiple technology adoption. Thus, peer to peer involvement may stimulate greater adoption of dairy technologies. Thus, the use of farmer-to-farmer approaches to enhance communication about various technologies, their specific needs and the benefits the technologies may have on dairy production efficiency would be good to study in further research work.

Lack of education and lack of work experience both have a negative association with multiple technology adoption, similar, to having limited or no work experience in dairy farming. This may suggest that with no education the farmer is less likely to be aware of the potential adverse effects less use of technologies may have on dairy production, i.e., milk yield, herd health and overall dairy production. While no to less working experience farmers are less likely to be aware of existing technologies, may have their level of literacy as a barrier or have not had enough time to obtain information from sources (informal and formal) on various technologies that may be beneficial. Access to female workers has a positive association with the adoption of a greater number of dairy technologies. Hiring or using more female workers is associated with an increase in the adoption of multiple dairy technologies. The larger the herd size the more dairy technologies were adopted, and the farmers with greater resources were better able to afford the technology and fully utilize it. This result is consistent with previous findings.

5. Discussion

Dairy production in Ethiopia comprises mainly smallholder farming systems managing cattle in traditional ways and research on these systems offers an opportunity for developing recommendations that can lead to livelihood improvement at household, community and national scales (Mekonnen et al., 2010). The adoption of multiple technologies in smallholder dairy farming remains a promising strategy in Ethiopia to improve farm productivity, farm incomes and reduce poverty improving food security and ensuring environmental sustainability (Zegeye et al., 2022). Dairy production technologies such as breed improvement, milking, forage and feed conservation, biosecurity, and animal health and food safety interventions have the potential to improve milk yields and quality of production, reduce disease prevalence and improve food safety (Mekonnen et al., 2010;

TABLE 4 Pairwise correlation of the 19 technologies explored in this study.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
(1) Breed improvement	1.000																		
(2) Improved housing	−0.037	1.000																	
(3) Biosecurity	−0.024	0.508***	1.000																
(4) Veterinary visit	0.046	0.495***	0.487***	1.000															
(5) Fencing	0.055	0.027	−0.037	−0.011	1.000														
(6) Disease test	−0.012	0.503***	0.320***	0.474***	0.002	1.000													
(7) AI breeding	0.112	0.106	0.025	0.039	0.004	0.165**	1.000												
(8) Recording deaths	0.176**	0.187**	0.209***	0.145*	−0.082	0.140*	0.025	1.000											
(9) Using home grown feeds	−0.014	0.124	0.052	0.186**	0.011	0.041	−0.094	0.107	1.000										
(10) Using commercial feeds	0.118	0.054	0.005	0.062	0.042	0.088	0.180**	0.129*	0.074	1.000									
(11) Using milking containers	0.090	0.201**	0.071	0.366***	0.022	0.147*	−0.110	0.308***	0.177**	0.015	1.000								
(12) Disinfecting teats	−0.020	−0.525***	−0.358***	−0.491***	0.115	−0.539***	−0.115	−0.077	−0.035	−0.110	−0.099	1.000							
(13) DCT	−0.005	0.307***	0.348***	0.282***	0.012	0.314***	0.023	0.139*	0.130*	0.093	0.127	−0.290***	1.000						
(14) Vaccination	0.094	−0.109	−0.002	0.027	0.020	−0.209***	−0.098	0.053	0.043	−0.053	0.111	0.210***	−0.118	1.000					
(15) Keeping health records	0.136*	0.279***	0.262***	0.201**	−0.172**	0.189**	0.008	0.617***	0.179**	0.157**	0.276***	−0.099	0.251***	0.032	1.000				
(16) Using disinfection footbaths	0.051	0.633***	0.399***	0.372***	0.097	0.456***	0.211***	0.202**	0.104	0.135*	0.125	−0.470***	0.266***	−0.148*	0.253***	1.000			
(17) Control of worms	0.094	−0.046	0.053	−0.035	−0.076	0.101	−0.019	−0.002	−0.076	−0.053	0.038	0.009	0.031	0.058	−0.077	−0.088	1.000		
(18) Control of ticks	0.044	0.121	0.111	0.042	0.138*	0.147*	0.032	0.051	0.272***	−0.048	0.136*	0.004	0.161**	0.118	−0.019	0.156*	0.118	1.000	
(19) Use of zero grazing	0.213***	−0.007	−0.110	−0.121	−0.058	−0.040	0.227***	0.165**	−0.180**	0.182**	−0.002	0.065	−0.062	0.001	0.116	0.031	0.001	−0.013	1.000

*$p<0.05$, **$p<0.01$, ***$p<0.001$.

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TABLE 5 Summary statistics of the variables used in the regression.

Variable	Mean	Standard deviation	Min	Max
Technologies	11.04	2.88	4	19
Age	41.65	12.73	20	89
Age squared	1896.09	1198.64	400	7,921
Number of cows	16.53	17.89	0	99
Bishoftu farm location	0.14	0.35	0	1
Bole farm location	0.19	0.39	0	1
Kaliti farm location	0.09	0.29	0	1
Ketema farm location	0.04	0.19	0	1
Kolfe farm location	0.04	0.21	0	1
Holeta farm location	0.21	0.41	0	1
Sebeta farm location	0.17	0.38	0	1
Sendafa farm location	0.11	0.32	0	1
No education	0.06	0.23	0	1
Primary education	0.31	0.47	0	1
Secondary education	0.38	0.49	0	1
Tertiary education	0.25	0.43	0	1
Number of female workers	1.31	2.60	0	19
Number of male workers	3.11	5.66	0	35
No years of experience	0.23	0.42	0	0
1–5 years of experience	0.24	0.43	0	1
6–7 years of experience	0.14	0.35	0	1
More than 10 years of experience	0.38	0.49	0	1
Trust government information	0.91	0.28	0	1
Trust information from government agencies	0.93	0.25	0	1
Trust information from other farmers	0.82	0.38	0	1
Perceived fellow farmers as peers	0.72	0.45	0	1
Membership to farmer organizations/groups	0.23	0.42	0	1
Additional income	0.21	0.41	0	1

Kumar et al., 2016; Burkitbayeva et al., 2019; Janssen and Swinnen, 2019). While extant literature has explored the adoption of technologies in Ethiopia, this has mostly focused on crop production systems, with limited studies considering dairy production systems, and specifically the intensity of adopting multiple technologies simultaneously. There are different technologies available for dairy farmers such as those considered in this research namely animal housing, mechanisms to improve milking hygiene and storage, and use of emergent technologies at the farm level in SSA such as animal electronic identification (EID) for farm management, artificial insemination (AI) and embryo transfer, cattle surveillance, welfare qualitative behavioral assessment, anaerobic digestion, pedometers or activity monitors to detect oestrus and increase fertility/conception, and webcams, smartphones/tablets for animal husbandry (Kumar et al., 2011, 2017; Liu et al., 2019). Animal health technologies including improved housing, veterinary visits and biosecurity measures could reduce disease pressures in smallholder dairy farming systems, reduce the reliance on antibiotics, reduce zoonotic risk and have the potential for anti-microbial resistance. Indeed, the adoption of animal health technologies such as preventive and curative measures including vaccine technology, internal and external parasitic remedies technology, disinfectants technology and veterinarian's services have been shown to have positive farm-level outcomes (Sarrazin et al., 2014; Ritter et al., 2016). The adoption of technologies related to food safety measures could improve milk quality and reduce the public health risks associated with milk-borne illnesses (Kumar et al., 2011, 2017). There is a paucity of research on the adoption of food safety measures at the farm level in developing countries (Mekonnen et al., 2010; Kumar et al., 2017), so further research is needed.

The aim of this study was to examine the degree of adoption of 19 different dairy technologies/practices singularly and together. The objectives of the study are to identify the factors that influence multiple adoption, described herein as adoption intensity, as well as seeking insight into the types of farmers most likely to adopt multiple dairy technologies simultaneously. The adoption of improved technology promises to improve dairy production, animal and human population health and improve efficiency in smallholder dairy farming systems (Zegeye et al., 2022). The least adopted technologies identified in this research were a biosecurity plan (44%), record keeping of farm mortality (44%), growing feed/forage on the farm (30%), disinfection footbaths (28%), veterinary visits (27%), improved housing (25%), milking and storage improvements (17%), dry cow therapy (16%), and testing new cattle before introducing them to the herd (14%). Adopting these practices more widely would have an immediate effect on productivity and financial returns. Further research should consider why there is low adoption of these technologies, both individually and together. The levels of literacy identified in this study may affect intentions to adopt documentation and access to resources including financial capital could affect adoption strategies. This should be explored further.

The adoption of forage technology, feed/forage conservation and feeding management by smallholder dairy farmers promises to be an alternative feed/forage source to the traditional teff straw and native pastures and can improve animal nutrition and reduce labor requirements of feeding cattle (Ashley et al., 2018). Animal health, cattle housing and biosecurity practices, internal and external parasitic remedies, and vaccines can reduce cattle disease burden, livestock mortality and mitigate greenhouse gas emissions and improve productivity. Improved animal health and welfare and associated increases in yields could better meet increasing milk demand, reducing motivation and opportunities for milk adulteration (Janssen and Swinnen, 2019). The adoption of hygienic milking and storage and hygienic food handling measures could improve milk quality and reduce the public health risks associated with milk-borne illnesses (Kumar et al., 2011, 2017).

Adoption of technology is limited on some farms (see Table 1) and is dependent on socio-economic conditions. Age is one such factor that determines technology adoption behavior. Dehinenet et al. (2014) findings show that the age of the household head has a negative significant association with the probability of adoption and degree/

TABLE 6 Coefficient and marginal effect estimates of the negative binomial regression.

Variables	Coefficient (β)	Marginal effects dy/dx
Age	−0.003 (0.007)	−0.038 (0.073)
Age squared*10^2	0.004 (0.007)	0.042 (0.079)
Number of cows	0.00565*** (0.001)	0.0614*** (0.010)
Bishoftu farm location	0.069 (0.057)	0.766 (0.650)
Bole farm location	0.095 (0.055)	1.066 (0.631)
Kaliti farm location	0.050 (0.048)	0.558 (0.537)
Ketema farm location	0.156 (0.082)	1.827 (1.030)
Kolfe farm location	0.183** (0.056)	2.158** (0.715)
Sebeta farm location	0.103 (0.057)	1.159 (0.669)
Sendafa farm location	−0.154* (0.060)	−1.575** (0.580)
No education	−0.168** (0.065)	−1.698** (0.609)
Primary education	−0.067 (0.052)	−0.721 (0.549)
Secondary education	−0.069 (0.042)	−0.743 (0.452)
Number of female workers	0.0169*** (0.005)	0.184*** (0.050)
Number of male workers	0.004 (0.002)	0.038 (0.026)
No years of experience	−0.134* (0.056)	−1.407* (0.572)
1–5 years of experience	0.028 (0.052)	0.305 (0.570)
More than 10 years of experience	−0.022 (0.048)	−0.236 (0.518)
Trust government information	−0.103 (0.062)	−1.167 (0.728)
Trust information from government agencies	0.143** (0.052)	1.466** (0.500)
Trust information from other farmers	0.013 (0.047)	0.140 (0.503)
Perceived fellow farmers as peers	0.132* (0.051)	1.389** (0.529)
Membership in farmer organizations/groups	−0.021 (0.044)	−0.223 (0.472)
Additional income	0.028 (0.043)	0.309 (0.471)
Constant	2.228*** 0.171	
Inalpha	−34.07	
N	159	

*$p<0.05$, **$p<0.01$, ***$p<0.001$. *** indicates the variable is significant at the 0.01 level; ** indicates the variable is significant at the 0.05 level; * indicates the variable is significant at the 0.10 level. Values in parentheses are standard errors of the estimate. Marginal effects are computed at the means of the Xs. (*) dy/dx is for discrete change of dummy variable from 0 to 1.

extent of adoption of dairy technologies. Our findings do not show any significant relationship however for the sample population, this may be due to the limitation of having a small sample size, or the purposive and convenience based sampling undertaken. Consequently results from the binary logistic model indicate farm knowledge, accessibility of extension services, gender, farm size, farming experience, and crossbreeds' availability had a positive association with dairy technology adoption, while age and market distance had a negative association (Abbasi and Nawab, 2021).

Trust in information from government agencies was associated with a higher propensity to adopt multiple technologies as was farmer perception of fellow farmers as peers. How they perceive their fellow farmer is important to note as it has an impact on uptake and diffusion of technologies. Fox et al. (2021) findings suggest that farmers look to their peers for advice prior to making a decision on whether or not to adopt technology. Other studies have shown that farmers within a social group learn from each other more fully the benefits and usage of new technology. For example, Uaiene Rafael (2011) suggests that social network effects are important for individual decisions and that farmers share information and learn from each other in adopting agricultural innovation. This is an important finding as it may help policymakers or institutions explore knowledge exchange and diffusion of innovation strategies tailored to specific farming and community situations (Manning, 2013).

Farming experience is essential in dairy production. Specially, longer farming experience generally induces farmers to obtain more information about improved technologies and practices from informal sources, and information gathering from more formal sources is associated with greater exposure to demonstrations or training and membership in farmers groups or cooperatives (Kumar et al., 2020). Past studies have shown that larger-sized farms are generally more likely to adopt technology than smaller ones (Rahelizatovo and Gillespie, 2004). The adoption of new technology often involves substantial initial capital investment, and farmers with greater resources are better able to afford the technology and fully utilize it, and also to derive the maximum benefit. Technology adoption rates increased significantly with increased education level and herd size (Rahelizatovo and Gillespie, 2004; Mekonnen et al., 2010; Kumar et al., 2020). Studies reported here suggests that the interactions could be nuanced, and further research is required to understand the interaction of socioeconomic factors more clearly.

6. Conclusion and policy implications

Smallholder dairy production systems in SSA countries are characterized by low productivity and a low rate of technology adoption. The adoption of modern technologies, singularly or multiple technologies, has been seen to improve farmers' productivity, the welfare of farmed animals, personal farmers' livelihoods, and can potentially drive rural development and poverty reduction. Although the use of technology has increased in recent years, the adoption and diffusion rate of modern technology in the dairy sector in Ethiopia and other countries has been low and slow. The need to stimulate and promote adoption intensity, therefore, is clear and needs to be addressed. The adoption of multiple technologies in dairy farming, from the 19 examined here, remains a promising strategy in Ethiopia for improving the welfare of rural households, reducing poverty, improving food security and ensuring environmental sustainability, but uptake of individual technologies across the sample group of farmers differs greatly. There is limited knowledge in SSA, particularly in East Africa, of what technologies smallholder dairy farmers are adopting and the factors influencing farmer adoption decisions. Therefore, this study sought to address this knowledge gap. Our study variability in both the number of technologies adopted and the types of technologies chosen. Economic return is a driver and the focus is on utility in a given context within a farming business. Differentiated uptake of technology based on socio-demographic factors including farm location, suggests a range of factors of influence including access. At one end of the scale, less than one in five farmers had adopted technologies such as containers used for milking and storage, dry cow therapy, and testing new cattle before introducing them to the herd. However there was clear strong uptake for technologies that addressed breeding, good nutrition, vaccination and parasite control and disinfection of teats both individually and combined. The findings show trust mediates farmers' decision making on technology adoption especially peer-to-peer trust networks and this is worthy of further study. This study has implications for policy, knowledge exchange and strategies to continue to improve productivity, disease controls and public health in the dairy production in Ethiopia. This study has policy implications beyond Ethiopia. The particular factors of the size of the dairy sector as well as challenges with endemic disease made Ethiopia an interesting lens through which to explore technology adoption, but the findings can be generalized to other countries with similar challenges. Developing guidance programs which can be disseminated through trusted knowledge brokers is essential to increase uptake especially technologies that have low cost implications. This is essential in promoting appropriate disease control strategies as if some farmers do not engage this will mean their farms may harbor zoonoses making them far more difficult to eradicate. The lack of uptake of some of the food safety and food quality interventions also raises concerns about the impact on public health programs. If there is a limited supply chain driver for improving food safety then this will need to be driven more fully at regulatory level. While, previous work has identified that the adoption of modern agricultural technologies in Ethiopia's dairy production system has multiple socio-economic benefits, this study shows that the take-up of such technologies is not consistent limiting the benefits that can be derived. This study would propose that further work needs to be undertaken to increase uptake with a clear focus on geographic differences, and greater knowledge and technology exchange to drive greater adoption intensity.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Dynamic diffusion of hybrid rice varieties and the effect on rice production: evidence from China

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The widespread adoption of hybrid rice varieties in China is a successful example, showing the role of agricultural technology in terms of food security. However, the dynamic diffusion of hybrid rice varieties and their effect on rice production requires further study. Based on data on hybrid rice adoption at the provincial level from 1984 to 2011, we applied the Ordinary Least Squares (OLS) and Geographically and Temporally Weighted Regression (GTWR) models to investigate the spatial and temporal effects of hybrid rice adoption at national and provincial levels. Overall, the effects of hybrid rice adoption on rice production have decreased over time. However, the results showed possible spillover and crowding effects of hybrid rice adoption across provinces. In particular, the development of hybrid rice varieties in Hunan province has had a significant influence on changes in rice yield and the distribution of rice areas in other regions. This study, therefore, serves as a reference in understanding the dynamic distribution of high-yield rice variety adoption in relation to food security and for designing appropriate agricultural extension strategies. However, further research is needed to identify the determinants affecting changes in rice farming in complex environments and associated ecological systems.

KEYWORDS

spatio-temporal effect, hybrid rice, variety adoption, GTWR model, China

1. Introduction

Food security is one of the Sustainable Development Goals (SDGs) to be achieved by 2030 for the benefit of the global community. It is critical that we satisfy the increasing demands of the growing population created by land and water are becoming more scarce and high crop productivity is required to achieve stable food production under climate change (Atlin et al., 2017). As the progress of the Green Revolution has shown, the development of modern agricultural technologies plays an important role in ensuring sufficient food supplies and contributing to economic growth (Rosegrant and Hazell, 2001; Spielman and Pandya-Lorch, 2009). Agricultural technologies include a variety of technologies such as varieties, agricultural inputs, and management practices, as well as corresponding land preparation practices (Feder et al., 1985; Zheng et al., 2021). Of these, crop variety is prioritized, as farmers' selection of a specific crop variety determines crop productivity and its variability (Spielman and Smale, 2017; Singh et al., 2020). The widespread adoption of modern varieties is the primary factor leading to yield growth. Both national and international research institutions have attempted to promote and facilitate the adoption of improved rice and wheat varieties (Lin, 1992; Fan et al., 2005; Yamano et al., 2016). However, the diffusion of varieties across regions and countries is uneven and unequal (FAO, 2002). Given that the development of plant breeding technology is vital to improving the yield potential of food crops, understanding the diffusion of modern varieties and its effect on food production is imperative for better and more efficient design of technology transfer systems (Qaim, 2020).

Rice is the main staple food for half of the global population and contributes substantially to farm household income and economic growth (Zeigler and Barclay, 2008; Spielman and Pandya-Lorch, 2009). High-yield varieties (HYVs) of rice have helped many developing countries meet the increasing food demand and achieve poverty reduction, and China is a successful example of the extraordinary progress that can be made (Fan et al., 2005; Mishra et al., 2016). Rice varieties include the hybrid bred rice variety and conventionally bred variety. The distribution of semi-dwarf rice varieties with high yield potential and the commercial dissemination of hybrid rice are the two most important achievements in rice research in China (Lin, 1992). Hybrid rice is a first-generation (F_1) crop developed by crossing two distantly related rice varieties, one of which is male (sterile). The range of yield advantage of hybrid rice is over 15–20% higher than that of conventionally bred rice (Ma and Yuan, 2015; Singh et al., 2018). The duration from the initiation of hybrid rice research by Yuan Longping in 1964 to large-scale hybrid seed production in 1975 and subsequent commercial production in 1976 was 10 years (Ma and Yuan, 2015; Singh et al., 2015). The rice cultivation area used to grow hybrid varieties accounted for over 60% of rice production and 52% of rice cultivation area in the 2000's (Fan et al., 2005; Spielman et al., 2012). The success of hybrid rice production in China, regarding both yield gain in the field and expansion of the sown area, has encouraged other developing countries to strive for growth in rice production (Mottaleb et al., 2015). The extent and progress of hybrid rice variety adoption and its impact on local and national rice production are thus helpful for a better understanding of the relationship between agricultural technology development and changes in rice farming in China.

The number of hybrid rice varieties released and certificated has increased tremendously in China in recent years. Approximately 300 new hybrid rice varieties are officially released every year, and hybrid rice varieties account for nearly 70% of the total rice varieties produced (Ma and Yuan, 2015). In total, over 490 hybrid rice varieties were widely adopted at farm level in 2011. The rapid development of hybrid rice varieties has spurredresearch on the breeding, management, and cultivation techniques, as well as the development of the seed industry in China, which has substantially expanded the hybrid rice area in the last few decades (Ma and Yuan, 2015; Yin et al., 2018). By 1984, all southern provinces[1] with rice-producing areas were growing hybrid rice varieties. However, the number of hybrid rice varieties and expansion of the hybrid rice area across the main rice-producing areas in China is uneven and unequal, which may raise concerns about resource wastage (Huang, 2022a). The yield advantage of hybrid rice plays an important role in ensuring national food supplies despite decreasing rice-cultivating areas in the last few decades and substantial changes in rice cropping patterns across different rice-producing areas (Chen et al., 2020). The adoption of hybrid rice varieties has led to changes in cropping patterns and contributed to the transition of food systems in emerging economies, and in this context, the spatial dimensions of technology diffusion help identify the spillover and crowding effects to implement improved extension strategies and achieve industry development (Ward and Pede, 2015; Huang, 2022a). With more types of male sterility being exploited, hybrid rice production in China has become more diversified (Cheng et al., 2007). The changes and relationship between variety adoption and land use as well as rice production are yet to be examined.

This study analyzed the changes in hybrid rice adoption in the main rice-producing provinces and evaluated the effect of hybrid rice adoption on rice production within the provinces and across regions. The contributions of the study are: first, taking the number of hybrid rice varieties as the variable, we mapped the changes in hybrid rice technology adoption in each rice-producing province from 1984 to 2011. China is a country that has successfully promoted long-term commercial hybrid rice production on a large scale. Detailed information on changes in hybrid rice technology development is helpful to better understand the diffusion and effects of variety adoption on total rice production. The results of the study provide a reference for other countries to design strategies for hybrid rice technology extension. Second, the effects of hybrid rice technology on rice production changes have remained an open question. The changes in cropping patterns in the main rice-producing provinces in China vary considerably. For instance, the share of double-cropping rice areas at the national level decreased substantially from 31% in 1984 to 20% in 2011. In Hunan province, it declined from 46% in 1984 to 36% in 2011; in contrast, the share almost remained constant in Jiangxi province. Although the wide adoption of hybrid rice varieties compensates for the reduction of the rice area in China, the effects of hybrid rice adoption on the

1 Regions in China are categorized into two types based on geographical and economic divisions. Geographically, China is divided into seven regions including northeast China, such as Heilongjiang, Jilin, and Liaoning, east China, such as Anhui, Fujian, Jiangsu, and Zhejiang, north China, such as Beijing, Hebei, and Shanxi, central China of Henan, Hubei and Hunan, south China, such as Guangdong, Guangxi, and Hainan, southwest China, such as Gansu and Shaanxi, and northwest China, such as Chongqing, Guizhou, Sichuan, and Yunnan. Economically, China is divided into four regions including the eastern regions, such as Guangdong, Jiangsu, and Zhejiang, the central regions, such as Anhui, Hunan, and Jiangxi, the western regions, such as Guangxi, Sichuan, and Yunnan, and the northeast region of Heilongjiang, Jilin, and Liaoning. We opted for the geographical division in the study.

rice area and production may vary across provinces. Evaluation of the impact of hybrid rice technology on rice production is thus important to understand these changes, specifically, both spatial and temporal effects, which need to be measured for a better understanding of the effects of variety adoption. Geographically and temporally weighted regression was applied to measure the effects caused by the time and space variables. Based on the results, the implications of seed commercialization and technology transfer system development for ensuring food security in China in the future are discussed, considering the relevance of this relationship for public policy and early work on the theoretical framework of induced innovation in agriculture.

This study is organized as follows: a literature review is presented in Section 2, followed by the section on data and methods. Section 4 presents the results, and Section 5 summarizes the implications based on the findings and draws a conclusion for the study.

2. Literature review

There is a rich body of literature examining the development and diffusion of hybrid rice technology in developing countries, and a large number of recent research projects have focused on the factors influencing the adoption of hybrid rice at the farm level (Cheng et al., 2007; Spielman et al., 2017). Very few studies are based on data at the macro level, which could provide the bigger picture of policy design. Hybrid rice has been widely adopted in China, India, Bangladesh, Vietnam, Indonesia, and other countries (FAORAP, 2014; Shah et al., 2016; Hu et al., 2022). Fan et al. (2005) found that the improvement in rice varieties has contributed to increases in rice production in China and India. Lin (1991a) studied the diffusion of hybrid rice with family samples from Hunan province, China, and examined the impact of the administrative intervention on farmers' decisions regarding hybrid rice adoption. Lin (1991b) found a significant positive effect of education on farmers' adoption of hybrid rice in Hunan. Similarly, Spielman et al. (2017) conducted a study based on a series of unstructured interviews to investigate the effect of an innovation system on hybrid rice development in India and Bangladesh. In China, planting pattern is an important factor affecting the adoption of hybrid rice (Huang et al., 2021). Chen and Chen (2011) found that the yield gain of super rice could have better market value and benefit farmers more than regular rice. Anwar et al. (2021) confirmed the potential of hybrid rice to increase productivity and farmers' income. However, most studies are based on household-level data, and the site-specific findings may be insufficient to show the dynamic changes of technology adoption in the long run across different regions (Lin, 1992; Wang et al., 2021; Huang, 2022a).

Changes in hybrid rice production and variety adoption vary across regions in China (Zeng et al., 2019). While the adoption of hybrid rice has contributed greatly to Chinese food security over the past 30 years, the distribution of hybrid rice production has become scattered and diversified (Cheng et al., 2007; Ma and Yuan, 2015). The spread of hybrid rice cultivation to different provinces and in different periods has been significantly different (Huang and Scott, 1993). In the early 1980's, the hybrid rice industry developed rapidly, and the sown area of hybrid rice was stable (Li, 2010). The number of combinations of major male sterile lines increased substantially with a few dominant lines, such as Zhenshan 97A, which accounted for 85% of the total number of combinations in China in 1990, after which its proportion declined (Mao et al., 2006). Hybrid rice is mostly grown in southern China as the area of cultivation is a main factor determining the intensity of hybrid rice adoption (Lin, 1992). The site-specific topography and diversified ecological conditions significantly affect the distribution of the hybrid rice area in Sichuan province (Luo, 1994). Xiao and Li (2014) found a spatial correlation between agricultural production in China, especially in the provinces, with similar agricultural technology adoption. Gao and Song (2014) discovered a trend in spatial convergence of technical efficiency in grain production in the process of technology extension, which may indicate the interaction of production across different producing areas. Taking rice seedling-throwing technologies as an example, Yu et al. (2017) found that a significant spillover effect existed among neighboring provinces. As a classic agricultural technology innovation in China, the effect of hybrid rice popularization and diffusion on regional rice production remains to be studied.

Econometric methods have been applied to investigate the spillover effect of technology diffusion. Spatial autocorrelation coefficients, like the Moran index, have often been used for impact evaluation (Mamiit et al., 2020; Zhang et al., 2021). Based on this index, the interrelationship of technological innovation among regions can be displayed vividly on geographical maps. However, the spillover effects across regions remain to be measured (Bjørkhaug and Blekesaune, 2013; Allaire et al., 2015). Xiao et al. (2022) used the spatial Durbin model (SDM) and threshold model to analyze the efficiency of agricultural green production following technological progress. Bao et al. (2021) used the spatial autoregressive (SAR) model to analyze the influencing factors of the total factor productivity of grain production. Spatial econometric models such as SAR and SDM incorporate spatial terms of dependent variables into the model, which may cause estimation bias due to the endogeneity. Thus, the spatial lag of the X (SLX) model, by introducing the spatial term of independent variables, has been suggested to correct this estimation bias (Halleck Vega and Elhorst, 2015). Besides, Brunsdon et al. (1996) proposed geographically weighted regression (GWR) as a local variation modeling technique to capture the spatial variation (Huo et al., 2022). To deal with both spatial and temporal heteroscedasticity simultaneously, a geographically and temporally weighted regression (GTWR) method has been adopted in this study for capturing interactions across different provinces in different years (Huang et al., 2010).

3. Data and methodology

3.1. Analytical framework

Rice production was first categorized into hybrid and conventional rice production to separate the effect of hybrid rice development on rice production in each area. Rice production in each province is presented as follows:

$$Prod_i = Prod^i_{HR} + Prod^i_{CR} = Area^i_{HR} \times Yield^i_{HR} + Area^i_{CR} \times Yield^i_{CR} \quad (1)$$

where i represents a specific rice-producing province. The subscripts, HR and CR, refer to hybrid rice and conventional rice, respectively.

Rice is widely grown in China under different production systems and climates ranging from warm sub-tropics to cool temperate climates with the center of the rice-cultivating area moving from southern China to northeast China (Fang and Sheng, 2000; Deng et al., 2019). The expansion of the rice-cultivating area in certain regions of China is crucial to increase national rice production despite a reduction in the total cultivating area (Liu et al., 2013). We assume that the development of hybrid rice production not only affects the conventional rice production within the same province but also both hybrid and conventional rice production in other provinces. From the perspective of food security, both hybrid and conventional rice can be viewed as substitute goods. We thus assume that the substitution effect between hybrid rice and conventional rice in a given province is α_i and the effect may vary across provinces as the levels of input and output of rice production in different provinces are different. The equation was presented as follows:

$$Prod^i_{CR} = \alpha_i Prod^i_{HR} \quad (2)$$

where α_i is the function of hybrid rice and conventional rice production within and outside the given province, which is presented as:

$$\alpha_i = h\left(Prod^i_{HR},\ Prod^i_{CR},\ Prod^{j-i}_{HR},\ Prod^{j-i}_{CR}\right) \quad (3)$$

The development of hybrid rice varieties in the i^{th} province is likely to affect the rice yield in other provinces as improved and new hybrid rice varieties can be introduced and adopted in different provinces through different ways, such as collaborative breeding programs, technology diffusion systems, seed companies, and farmers' seed exchanges. Therefore, the rice yield in one province could be affected by both the variety adoption within and outside the province. Huang and Scott (1993) argued that Chinese farmers usually decide on variety selection (i.e., whether hybrid rice or conventional rice), cropping system (i.e., double cropping or single cropping pattern), and agricultural inputs right before the planting season begins; therefore, the variety adoption decision is an input rather than an output variable for rice farming. Rice yield is thus presented as the function of variety adoption as follows:

$$Yield^i_{HR} = f(HR_i, HR_{j-i}, \mathbf{X}) \quad (4)$$

$$Yield^i_{CR} = g(CR_i, CR_{j-i}, \mathbf{X}) \quad (5)$$

where i and j refer to the i^{th} and j^{th} province, and $\mathbf{X}$ refers to the agricultural inputs.

Taking the equations into the function, Equation (1) can be transformed as follows:

$$\begin{aligned} Prod_i &= Prod^i_{HR} + Prod^i_{CR} = (1+\alpha_i)Prod^i_{HR} \\ &= [1 + h\left(Prod^i_{HR},\ Prod^i_{CR},\ Prod^{j-i}_{HR},\ Prod^{j-i}_{CR}\right)]Prod^i_{HR} \end{aligned} \quad (6)$$

and

$$Prod^i_{HR} = Area^i_{HR} \times Yield^i_{HR} = Area^i_{HR} \times f\left(HR_i, HR_{j-i}, \mathbf{X}\right) \quad (7)$$

$$Prod^i_{CR} = Area^i_{CR} \times Yield^i_{CR} = Area^i_{CR} \times g\left(CR_i, CR_{j-i}, \mathbf{X}\right) \quad (8)$$

Furthermore, we assumed that the rice area in the i^{th} province can be described as the function of rice yield and agricultural inputs, which is $Area^i_{HR} = A(Yield^i_{HR}, Yield^i_{CR}, \mathbf{X})$.

Total rice production in the i^{th} province is affected not only by the development of rice varieties locally but also by those in other provinces. Rice production in the i^{th} province can be transformed into the function of the development of different rice varieties and agricultural inputs, that is:

$$Prod_i = F(HR_i, CR_i, HR_{j-i}, CR_{j-i}, \mathbf{X}) \quad (9)$$

where HR_i and CR_i refer to the development of hybrid rice and conventional rice varieties in the i^{th} province. HR_{j-i} and CR_{j-i} represent the hybrid and conventional rice varieties in other provinces excluding the i^{th} province.

3.2. Model specification

The specification of rice production in a given province is assumed to be a function of local technology development (measured by the number of hybrid and conventionally bred rice varieties) and agricultural inputs and described as follows, without considering the interaction effect from other provinces:

$$Y_{it} = \beta_0 + \beta_{1i}HR_{it} + \beta_{2i}CR_{it} + \beta_{3i}HR_{it} \times CR_{it} + \mathbf{X}'\boldsymbol{\theta} + \mu_i + \varepsilon_{it} \quad (10)$$

where Y_{it} denotes the rice production of the i^{th} province in the t^{th} year, which is measured by the variable of production (*prod*), area (*area*), and yield (*yield*) separately in the models. HR_{it} represents the number of hybrid rice varieties adopted by farmers in the i^{th} province in the t^{th} year. CR_{it} represents the number of conventional rice varieties adopted by farmers in the i^{th} province in the t^{th} year. $\boldsymbol{X}$ is a vector of the control variable, including agricultural inputs and rice cropping pattern, which is measured by the share of the sown area of double-cropping rice (*doublecrop*), the number of agricultural laborers (*agrlabor*), total fertilizer expenditure in rice farming (*fert*), the irrigated rice area (*irri*), and the damaged rice area due

TABLE 1 Summary of statistics of variables included in the empirical analysis.

Variables	Overall (1984–2011)		Period I (1984–1991)		Period II (1992–2001)		Period III (2002–2011)	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Yield (t/ha)	5.92	1.00	5.37	0.89	6.06	0.94	6.22	0.98
Sown area (million hectares)	2.24	0.97	2.50	1.03	2.27	0.90	2.01	0.95
Rice production (million tons)	13.37	6.21	13.72	6.40	13.85	6.00	12.61	6.24
The number of hybrid rice varieties	32.84	36.77	8.27	5.17	21.78	14.53	63.57	44.84
The number of conventional rice varieties	18.01	11.62	21.07	11.14	16.48	11.78	17.08	11.46
Share of sown area of double-cropping rice (%)	25.96	20.06	28.56	20.37	27.50	20.12	22.34	19.39
Rice effective irrigated area (million hectares)	0.73	0.36	0.80	0.38	0.71	0.34	0.69	0.35
Rice disaster area (million hectares)	0.61	0.38	0.66	0.40	0.65	0.37	0.53	0.36
Numbers of agricultural workers (million people)	16.53	7.26	17.06	7.93	17.49	7.64	15.13	6.07
Total fertilizer expenditure for rice (million dollars)	14.88	6.49	15.39	6.68	15.08	6.21	14.28	6.62

Data source: China Rural Statistical Yearbook, Chinese data from the Farm Production Costs and Returns Survey (FPCRS), Ministry of Agriculture and Rural Affairs.
The Chinese yuan is converted to United States dollars (USD) using the exchange rates for 1 USD in 2022: CNY (7).

to disasters (*disarea*) (Table 1). β_{1i}, $\beta_{2i,}$ β_{3i}, and $\boldsymbol{\theta}$ are the coefficients to be estimated. μ_i represents the province fixed effect, and ε_{it} is the random error term. In addition, we applied a technique of applying clustering standard errors to deal with the possible cross-sectional heteroskedasticity (Bertrand et al., 2004; Huang, 2017). We corrected the standard errors for clustering by province cell.

In addition to the local adoption of rice varieties, rice production in a given province could be affected by the spillover effects of rice production in other provinces. Farmers in a province tend to adopt the same type of rice varieties if they have knowledge and access to those varieties with considerable yield gain that are widely adopted by farmers in another province. Spillovers of farmers' knowledge of variety adoption result in spatial effects across farmers (Ward and Pede, 2015). The above specification can be extended to the following equation by introducing the interaction effects from other rice-producing provinces.

$$Y_{it} = \beta_0 + \beta_{1i}HR_{it} + \beta_{2i}CR_{it} + \beta_{1j}HR_{jt} + \beta_{2j}CR_{jt} + \beta_{3i}HR_{it} \times CR_{it} + \mathbf{X}^{'}\boldsymbol{\theta} + \varepsilon_{it} \tag{11}$$

where i and j refer to the given province and other rice-producing areas, respectively. As the effects of rice production in different provinces in the given province may be varied, a spatial weight is assigned to each province. The sum of weighted effects aims to show the overall effect from other areas. The equation can be rewritten as follows:

$$Y_{it} = \beta_0 + \sum_{j=1}^{m} \beta_{1j} w_{ij} \times HR_{jt} + \beta_{2i}CR_{it} + \beta_{3j} \sum_{j=1, j\neq i}^{m} w_{ij} \times CR_{jt} + \sum_{k=1}^{K} \theta_k x_{ik} + \varepsilon_{it} \tag{12}$$

where m refers to the number of rice-producing provinces and w_{ij} is the spatial weighted effect of rice production in the j^{th} province on that in the i^{th} province. Based on the laws of geography (Tobler, 1970), the spatial weight was measured by the reciprocal value of distance. Therefore, if $j = i$, then w_{ij} refers to the effect of technology development on rice production in the same province, i.e., $w_{ij} = 1$. If $j \neq i$, then $w_{ij} = 1/D_{ij}$.

The effects of technology development in a given province on rice production in other areas may also vary across provinces due to the diversified economic and environmental conditions as well as different distances. Following the methods provided by Brunsdon et al. (1996), the geographically weighted regression (GWR) model was introduced to estimate specific local coefficients for each province by extending the traditional regression framework as follows:

$$Y_{it} = \beta_0(u_i, v_i) + \sum_{j=1}^{m} \beta_{1j}(u_i, v_i) w_{ij}HR_{jt} + \beta_{2i}(u_i, v_i) CR_{it} + \sum_{j=1, j\neq i}^{m} \beta_{3j}(u_i, v_i) w_{ij}CR_{jt} + \sum_{k=1}^{K} \theta_k(u_i, v_i) x_{ik} + \varepsilon_{it} \tag{13}$$

where (u_i, v_i) denotes the coordinates of the center in the i^{th} province (i=*1,…,m*), $\beta_0(u_i, v_i)$ is the intercept value, and

$\beta_{1j}(u_i, v_i)$ is a set of coefficients to measure the effects of technology development in other areas on rice production in the i^{th} province. $\beta_{2i}(u_i, v_i)$ and $\beta_{3j}(u_i, v_i)$ are coefficients to be estimated to identify the local and interaction effects of conventionally bred rice varieties in the i^{th} province, respectively. The coefficient estimated in this model varies across provinces, which allows for the identification of local effects (Huang et al., 2010). However, the effects of technology development on rice production change over time, which results in temporal heterogeneity. Taking the method introduced by Huang et al. (2010) as a reference, a GTWR model was used to capture both the spatial and temporal heterogeneity of rice technology development in rice production. The equation is presented as follows:

$$\begin{aligned} Y_{it} &= \beta_0(u_i, v_i, t_i) + \sum_{j=1}^{m} \beta_{1j}(u_i, v_i, t_i)\, w_{ij} HR_{jt} + \beta_{2i}(u_i, v_i, t_i)\, CR_{it} \\ &+ \sum_{j=1, j\neq i}^{m} \beta_{3j}(u_i, v_i, t_i)\, w_{ij} CR_{jt} + \sum_{k=1}^{K} \theta_k(u_i, v_i, t_i)\, x_{ik} \\ &+ \varepsilon_{it} \end{aligned} \tag{14}$$

The estimates of $\beta(u_i, v_i, t_i)$ are coefficients for each variable with space-time location; (u_i, v_i, t_i) presents the coordinates of the time-space location for the i^{th} province. The estimation of $\beta(u_i, v_i, t_i)$ can be estimated using ordinary least square regression and expressed as follows based on Huang et al. (2010):

$$\hat{\boldsymbol{\beta}}(\mu_i, \nu_i, t_i) = [\mathbf{X}^{\mathbf{T}}\mathbf{W}(\mu_i, \nu_i, t_i)\mathbf{X}]^{-1}\mathbf{X}^{\mathbf{T}}\mathbf{W}(\mu_i, \nu_i, t_i)\mathbf{Y} \tag{15}$$

where $W(\mu_i, \nu_i, t_i)$ is the space-time weighted matrix. In the space-time coordinate system, it is assumed that the effect of observed data "close" to the given i^{th} province has a greater influence than those located farther from the i^{th} province. In this sense, both temporal closeness and spatial closeness need to be defined and measured in the GTWR model (Huang et al., 2010). The spatio-temporal distance function of d_{ij}^{ST} and spatio-temporal weight matrix w_{ij}^{ST} are thus defined based on the space-time function and Gaussian distance-decay-based functions method as follows:

$$d_{ij}^{ST} = \sqrt{\gamma[(\mu_i - \mu_j)^2 + (\nu_i - \nu_j)^2] + \delta(t_i - t_j)^2} \tag{16}$$

$$w_{ij}^{ST} = \exp\left\{-\left(\frac{\gamma[(\mu_i - \mu_j)^2 + (\nu_i - \nu_j)^2] + \delta(t_i - t_j)^2}{b_{ST}^2}\right)\right\} \tag{17}$$

Of them, t_i and t_j are observed times at locations i and j and b^{ST} is a coefficient of spatio-temporal bandwidth, which is defined and measured by the cross-valuation method (CV) by Fotheringham et al. (2002). The bandwidth is estimated when the least square error is calculated.

$$CV = \sum_{i}^{n} [y_i - \hat{y}_i(b)]^2 \tag{18}$$

3.3. Data

The socioeconomic and agricultural input data were obtained from the *China Rural Statistical Yearbook* and Chinese data from *the Farm Production Costs and Returns Survey (FPCRS)*. The number of rice varieties released and adopted by the farmers was obtained from the *Ministry of Agriculture and Rural Affairs*. The data used in the study covered the period from 1984 to 2011 (Table 1). The total fertilizer expenditure in rice production was deflated by a price index, which was constructed using regional retail price indexes of farm inputs (Tian and Wan, 2000). The number of rice varieties adopted by farmers was the mega varieties with a sown area of over 100,000 *mu* (around 6,667 hectares). In total, the rice area planted with mega varieties including hybrid and conventional rice varieties accounted for 43.7 and 31.8% of the national rice area in 2011, respectively.

Rice was widely grown in 14 provinces in China in 2011. Heilongjiang and Jilin provinces are located in northern China without hybrid rice; therefore, the two provinces were not included in the study. In total, 12 provinces with both hybrid and conventional rice production were included. Of them, four provinces were selected to compare the site-specific effects of technology adoption on rice production: Hunan province, Jiangxi province, Guangdong province, and Sichuan province (Figure 1). Hunan was taken as the start and center of hybrid rice development. Jiangxi province is located in central China and is well-known for having the biggest rice-cultivating area associated with the double-cropping system. Sichuan province, located in northwest China with a low economic development level, has a large-scale hybrid rice seed production and variety adoption level. Guangdong province, located in southern China, is regarded as a developed area with a large rice-cultivating area. The four provinces accounted for ∼2-5ths of the national rice cultivation area and rice production in 2011. In terms of hybrid rice production, the four provinces accounted for over 80% of hybrid rice varieties and more than half of the hybrid rice area in 2011 (Table 2). Overall, the share of the hybrid rice-cultivating area of the total rice-cultivating area increased from 23.4% in 1984 to 43.7% in 2011. The development of hybrid rice areas varied across provinces. In 2011, the hybrid rice area accounted for 52.3, 55.6, 45.2, and 78.1% of the local rice area in Hunan, Jiangxi, Guangdong, and Sichuan provinces, respectively (Table 2).

4. Results

4.1. Trends of rice production in China

Rice production in China increased from 178.3 million tons in 1984 to 202.9 million tons in 2011 (Table 2). The improvement of rice yield played an important role as the total rice-cultivating area decreased. The share of double-cropping rice areas decreased from over 30% in 1984 to 20% in 2011. Rice yield improved quickly between 1992 and 2011, while the national rice-cultivating area declined. However, the changes in rice production in different provinces varied. The share of double cropping in rice-cultivating areas in Jiangxi province was almost constant in the past few decades, while the total rice area in Jiangxi was maintained at over

FIGURE 1
Distribution of main rice-producing provinces in China. To keep the consistency of data caliber, the data of Chongqing and Hainan were merged into Sichuan and Guangdong respectively.

3.3 million ha. In Hunan, which is well-known for its development of hybrid rice production, the share of double-cropping rice area decreased from 46% in 1984 to 36% in 2011, while the rice-cultivating area reduced from 4.4 million ha in 1984 to 4.2 million ha in 2011. Although Hunan and Jiangxi are two neighboring provinces with similar climatic conditions and economic levels, the changes in their rice production are different. Guangdong province experienced a significant reduction in its rice-cultivating area, declining from 3.5 million ha in 1984 to nearly 2.2 million ha in 2011, although the share of double-cropping rice area declined by only 5%. The rice system in Sichuan province has been dominated by the single rice cropping system and the rice area declined from nearly 4 million ha in 1984 to 2.6 million ha in 2011.

Changes in rice yield have varied across rice-producing areas in China. Overall, China has achieved substantial progress in its yield improvement, and the average national rice yield increased from 5.4 t/ha in 1984 to 6.7 t/ha in 2011. Sichuan province had the highest rice yield for decades, with 6.4 t/ha in 1984 and 7.5 t/ha in 2011, which was much higher than in other provinces. The rice yield in Guangdong province was maintained at a stable level lower than the national yield level, of 5.1 and 5.5 t/ha in 1984 and 2011, respectively. The rice yield in Hunan province increased from 5.5 t/ha in 1984 to 6.3 t/ha, which was close to the national yield level. Similarly, Jiangxi province improved its rice yield from 4.5 t/ha (1984) to nearly 6 t/ha (2011). Due to the varied progress in rice yield, the contribution of rice production from individual provinces to national rice production changed considerably.

The development of hybrid rice varieties is considered to be one of the main achievements of agricultural technology development in rice production. Hybrid rice varieties are a typical type of HYVs with yield gain and potential advantages. In China, the number of mega hybrid rice varieties adopted by farmers increased by over 10-fold from 1984 to 2011. In the 1980's, only a few hybrid rice varieties were developed and adopted by farmers with a large area, which might be attributed to both the breeding technology and seed industry development. In 2011, the number of hybrid rice varieties adopted by farmers with large-scale adoption, i.e., a sown area not <100,000 *mu* (around 6,667 ha), was nearly 500. After 20 years since Mr. Yuan Longping developed the hybrid rice variety in 1976, the number of hybrid rice varieties adopted by farmers has increased tremendously. Hunan province accounted for nearly 40% of the number of mega hybrid rice varieties, followed by Jiangxi and Sichuan provinces. The number of mega hybrid rice varieties in Guangdong province was much less than that in the three provinces and accounted for 40% of that in Hunan province.

Compared to the development and widespread adoption of hybrid rice varieties, the share of hybrid rice area of the total rice sown area increased rapidly in the 1990's and gradually reached a peak by 2006. The share of rice area used for growing hybrid rice increased from 23% in 1984 to 44% in 2011, followed by a decline in the total rice-cultivating area. With the rapid development of hybrid rice varieties, conventional rice varieties also made considerable achievements. However, the development of conventional rice varieties has been much slower than that of

TABLE 2 Rice production and varietal adoption in the country and selected provinces.

Variables	National				Hunan				Jiangxi				Guangdong				Sichuan			
	1984	1992	2002	2011	1984	1992	2002	2011	1984	1992	2002	2011	1984	1992	2002	2011	1984	1992	2002	2011
Yield (t/ha)	5.37	5.80	6.19	6.69	5.49	5.79	5.98	6.33	4.49	4.94	5.21	5.89	5.10	5.36	5.65	5.51	6.35	7.15	7.29	7.51
Sown area (million hectares)	33.18	32.09	28.20	30.34	4.40	4.19	3.54	4.16	3.33	2.98	2.79	3.44	3.51	3.29	2.45	2.20	3.99	3.12	2.78	2.60
Share of double-cropping rice area (%)	31.28	28.49	23.28	20.16	45.65	47.04	42.47	35.74	43.40	46.75	45.43	43.82	56.56	46.08	54.30	52.41	1.50	1.41	0.11	0.02
Rice production (million tons)	178.26	186.22	174.54	202.88	24.17	24.23	21.19	26.34	14.93	14.74	14.52	20.26	17.93	17.62	13.82	12.10	25.34	22.29	20.24	19.53
Number of mega hybrid rice varieties	37	74	216	499	5	25	56	196	1	11	39	176	10	30	43	79	7	6	20	139
Share of hybrid rice area (%)	23.38	46.94	50.48	43.66	30.90	56.84	62.06	52.31	19.28	34.32	71.67	55.58	39.74	41.44	42.06	45.20	42.21	87.71	83.78	78.13
Number of mega conventional rice varieties	238	229	224	274	19	29	25	23	38	6	14	20	37	34	35	24	10	0	0	8
Share of conventional rice area (%)	43.30	32.44	26.66	31.79	29.64	33.65	20.31	23.01	57.69	10.80	6.03	9.51	43.89	42.51	34.40	21.98	19.60	0.00	0.00	2.67
GDP per capita (USD)	100	332	1,350	5,145	74	228	962	4,109	71	210	833	3,736	118	528	2,211	7,239	70	211	841	3,734

Data source: China Rural Statistical Yearbook, Chinese data from the Farm Production Costs and Returns Survey (FPCRS), Ministry of Agriculture and Rural Affairs.
The Chinese yuan is converted to United States dollars (USD) using the exchange rates for 1 USD in 2022: CNY (7).
The share of hybrid rice area is computed by the mega hybrid rice area to the total rice area.
The share of conventional rice area is computed by mega conventional rice area to the total rice area.

hybrid rice. An increasing number of hybrid rice varieties increased the hybrid rice-cultivating areas, which may have crowded out the planting of conventional rice varieties. On average, over 200 conventional rice varieties were adopted by farmers and these varieties accounted for <½ of the total rice cultivated areas, on average. Hybrid rice varieties have significant yield advantages over conventionally bred rice; however, the grain quality of hybrid rice is not as good as that of conventional rice (Hu et al., 2016), which may restrict the further expansion of hybrid rice-cultivating areas in the context of changing consumer demands. With better income and economic growth, Guangdong province was considered more developed than Hunan, Jiangxi, and Sichuan provinces. High-quality rice with good taste and aroma was preferred by local consumers and thus was given priority by local breeders. In contrast, the lower the level of economic development, the higher the adoption of hybrid rice varieties. Sichuan province is located in the northwest of China with lower economic development and its hybrid rice-cultivating area accounted for nearly 80% of the provincial rice area. Similarly, in Jiangxi province, the share of the hybrid rice area was 56%. However, the share of the hybrid rice-cultivating area of the total rice area in Guangdong province was the lowest, at <50%. With the rapid development of hybrid rice technology and the widespread adoption of hybrid varieties, the number of conventional rice varieties adopted by farmers has decreased along with a decrease in conventional rice-cultivating areas. Particularly in Jiangxi province, the share of conventional rice area decreased from 58% in 1984 to <10% in 2011. To some extent, this demonstrates a crowding out effect between hybrid rice and conventional rice technology adoption, especially in developing areas.

4.2. Effects of hybrid rice adoption on rice production at national and provincial levels

Table 3 shows the results of the effects of hybrid rice adoption on rice production. Four regressions using the OLS method were implemented to investigate the overall effects from 1984 to 2011 and three individual effects in different periods, i.e., effects in the periods of 1984–1991, 1992–2001, and 2002–2011. The number of hybrid rice varieties adopted by farmers had a significant positive effect on rice yield and rice production. Increased adoption of hybrid rice resulted in improved rice yield and an increase in rice production. However, the effect of hybrid rice adoption on the rice area was negative. Particularly, hybrid rice adoption reduced the rice-cultivating area in the first period of 1984–1991. The effects of hybrid rice adoption on yield were greater than that on rice production as the coefficients were bigger.

There was also an interaction between the adoption of hybrid rice and conventional rice technology, which may have affected local rice production as well. The results showed that the adoption of hybrid rice varieties usually had a direct impact on rice production as the estimated coefficients of interaction between hybrid rice adoption and conventional rice adoption were mostly smaller than those of hybrid rice adoption in the regressions. Average rice yield changed with different numbers of rice varieties adopted by farmers associated with the changes of the sown area due to the yield advantage of hybrid rice, i.e., a high level of hybrid rice variety adoption increased its sown area and consequently improved the local average rice yield. Such effects included the contribution of hybrid rice adoption and substitution effects of hybrid rice adoption on conventional rice. Because the coefficient of interaction variable in the overall model of hybrid rice adoption was −0.01 (Table 3, row 3, column 1) compared to the value of 0.20 (Table 3, row 1, column 1), the increase in the average national yield should mostly be attributed to the adoption of hybrid rice varieties.

Table 4 shows the results of the regression of the effects of hybrid adoption on rice yield, area, and production at the provincial level without considering the interaction effect of rice production across different areas. It was assumed that provincial rice production will be affected by local technology development and the results were based on Equation (10) using the OLS method. In a given province, the effects of local hybrid rice adoption on the changes in rice production are mixed. The increased number of hybrid rice varieties adopted by farmers in Hunan and Jiangxi provinces significantly contributed to the local rice yield increase. The estimated marginal effect of hybrid rice variety adoption in Jiangxi province was 0.28 (Table 4, column 3), which was the highest followed by 0.15 (Table 4, column 1) in Hunan province. Rice yield in Sichuan province was not affected significantly by the local hybrid rice variety adoption, which was probably related to the local high level of rice yield due to the desired climate conditions. Sichuan province has had the largest area for hybrid rice seed production for 20 years and accounted for one-fourth of the national area for hybrid rice seed production. The effect of hybrid rice adoption on rice yield in Guangdong province was insignificant, which may be due to the slow progress of hybrid rice adoption associated with the changes in the rice cropping system as well as the increasing demand regarding the quality of rice. Therefore, maintaining conventional rice production and rice yield may not be prioritized in Guangdong province as much as in other provinces.

Regarding the changes in rice-cultivating areas, local hybrid rice adoption has enlarged the rice area in Hunan province while reducing those in Guangdong and Sichuan provinces. The results of the effects of the interaction between hybrid rice and conventional rice adoption are mixed. Farmers with large-scale rice areas may benefit more from the yield-gain advantage of hybrid rice adoption. Both Hunan and Jiangxi provinces have a long history of rice production and are viewed as the center of rice production in China to ensure national food security. Rice production in these two provinces accounted for 23% of national rice production in 2011. Besides, Hunan province has led the hybrid rice variety breeding and extension programs, and the local government has also made great efforts to support the technology development (Zeng and Liu, 2006). Within Hunan province, the adoption of hybrid rice varieties has positively affected rice production but has had negative effects in Guangdong and Sichuan provinces. However, with Jiangxi being adjacent to Hunan province, the spillover effect of agricultural technology development in Hunan province could have affected rice production in Jiangxi province through technology development cooperation and/or farmers' exchange of seeds and so on (Jing et al., 2013). Without considering the interaction effects of hybrid rice adoption across the provinces, the effects of hybrid rice adoption on rice production can be biased.

TABLE 3 Effects of hybrid rice variety adoption on rice production at the national level using the OLS model.

Variables	Overall (1984–2011)			Model 1 (1984–1991)			Model 2 (1992–2001)			Model 3 (2002–2011)		
	Yield	Area	Prod	Yield	Area	Prod	Yield	Area	Prod	Yield	Area	Prod
HR	0.20***	−0.03**	0.06***	0.99***	0.24*	0.63***	0.26**	0.06	0.18***	0.13***	0.02	0.06**
	(0.03)	(0.01)	(0.01)	(0.36)	(0.12)	(0.18)	(0.11)	(0.05)	(0.05)	(0.05)	(0.02)	(0.02)
CR	−0.12***	0.05***	−0.00	−0.56***	0.18***	−0.01	−0.05	−0.02	−0.04*	−0.17	−0.06	−0.11*
	(0.03)	(0.01)	(0.02)	(0.20)	(0.06)	(0.08)	(0.06)	(0.02)	(0.02)	(0.10)	(0.05)	(0.06)
HRCR	−0.01	−0.00	0.03**	−0.82**	0.23**	−0.05	−0.08	−0.08**	−0.09**	0.13**	0.02	0.06***
	(0.03)	(0.01)	(0.01)	(0.32)	(0.10)	(0.14)	(0.06)	(0.03)	(0.03)	(0.05)	(0.02)	(0.02)
Doublecrop	−0.54***	0.29***	0.23***	0.07	−0.18	0.02	−0.23	0.22***	0.19**	0.29	−0.15	−0.06
	(0.09)	(0.04)	(0.04)	(0.49)	(0.15)	(0.23)	(0.18)	(0.07)	(0.07)	(0.23)	(0.10)	(0.11)
Agrlabor	0.35***	0.09***	0.18***	0.46***	−0.11*	0.04	−0.09	0.11**	0.08	0.09	0.02	0.00
	(0.09)	(0.03)	(0.03)	(0.17)	(0.06)	(0.06)	(0.22)	(0.05)	(0.10)	(0.31)	(0.08)	(0.10)
Fert	0.42***	0.14***	0.25***	0.11	0.15**	0.19**	0.31***	0.06*	0.16***	0.29*	0.20***	0.25***
	(0.06)	(0.04)	(0.04)	(0.12)	(0.06)	(0.08)	(0.06)	(0.03)	(0.04)	(0.16)	(0.05)	(0.06)
Irri	−0.80***	0.57***	0.24***	−0.43**	0.58***	0.38***	−0.63***	0.63***	0.41***	−0.47**	0.13	0.07
	(0.09)	(0.05)	(0.06)	(0.21)	(0.10)	(0.11)	(0.20)	(0.09)	(0.11)	(0.21)	(0.12)	(0.14)
Disarea	−0.14***	0.03*	−0.02	−0.13**	−0.03**	−0.06**	−0.11**	0.02	−0.03	−0.20***	0.01	−0.04
	(0.04)	(0.01)	(0.02)	(0.05)	(0.01)	(0.03)	(0.05)	(0.01)	(0.02)	(0.07)	(0.02)	(0.03)
_cons	0.00	0.00	−0.00	0.18	0.32***	0.38***	0.22***	0.04*	0.13***	0.17**	−0.24***	−0.17***
	(0.02)	(0.01)	(0.01)	(0.27)	(0.08)	(0.12)	(0.05)	(0.02)	(0.02)	(0.08)	(0.05)	(0.05)
No. of observations	336	336	336	96	96	96	120	120	120	120	120	120
Marginal effect of HR	0.196***	−0.034**	0.061***	0.769**	0.297***	0.611***	0.269**	0.070	0.193***	0.122***	0.015	0.055**

The results are based on Equation (10) using the OLS regression.
***, **, *Refers to the significance level of 1%, 5%, and 10%, respectively.
Standard errors are in parentheses and are computed by the clustering of the error term by province cell.
Marginal effects are computed by coefficients of HR and HRCR and the mean of CR.

The following section, therefore, presents the spatial and temporal effects of hybrid rice adoption for a better understanding of the impact of hybrid rice technology diffusion.

4.3. Spatio-temporal effects of hybrid rice adoption in the selected provinces

Taking the example of the four selected provinces, the results showed that the development of hybrid rice adoption in a specific province may have different effects on rice production in other areas. Table 5 shows the average interaction effects of hybrid rice adoption on rice production using the data at the provincial level by pair grouping regression using the OLS method. To include all rice-producing areas in the model and capture both the spatial and temporal heterogeneity of hybrid rice adoption, the GTWR model was applied to measure the effects. We found that the interaction effects among the four selected provinces were greater than others. The development of hybrid rice variety adoption in Hunan province had a greater and wider influence on rice production across different areas in terms of the value of estimated coefficients and the number of provinces being affected. In addition to the spatial effects of hybrid rice adoption, the temporal effects varied in different periods as well. Overall, the development of hybrid rice varieties in the 1990's has had a greater influence on rice yield improvement and rice production, which to some extent indicates that it takes several years, almost a decade, for a large-scale extension of hybrid rice varieties. In the 2000's, the increase in rice yield tapered down, which is consistent with the yield potential of variety breeding progress (Hu et al., 2016; Huang, 2022b).

4.3.1. Hunan province

In the 1980's and 1990's, the adoption of hybrid rice varieties in Hunan province had a reducing positive impact on rice yield in most rice-producing provinces (Figures 2A–C). The magnitude of changes varied across different provinces. For instance, the effect of hybrid rice variety adoption in Hunan on the rice yield of Sichuan province was 6.45 (Figure 2A) during 1984–1991 and decreased to 1.84 (Figure 2B) during 1992–2001, which was higher than those of other provinces. The effect became negative in the 2000's. In contrast, hybrid rice variety adoption in Hunan province always positively affected the rice yield in Guangdong province to a certain extent in the last few decades. From the diffusion of effects over time, the areas where rice yield was most affected by

TABLE 4 Effects of local hybrid rice variety adoption on rice production within the province using the OLS model.

Variables	Yield				Area				Production			
	Hunan	Sichuan	Jiangxi	Guangdong	Hunan	Sichuan	Jiangxi	Guangdong	Hunan	Sichuan	Jiangxi	Guangdong
HR	0.17***	0.32**	0.29***	0.07	0.09**	−0.12**	−0.02	−0.41*	0.20***	0.02	0.13***	−0.29
	(0.04)	(0.15)	(0.05)	(0.41)	(0.03)	(0.05)	(0.02)	(0.22)	(0.04)	(0.08)	(0.03)	(0.34)
CR	0.01	0.22	−0.03	−0.20	0.10	0.14	0.05**	−0.00	0.11	0.23*	0.03	−0.10
	(0.08)	(0.20)	(0.03)	(0.15)	(0.06)	(0.08)	(0.02)	(0.08)	(0.08)	(0.11)	(0.02)	(0.12)
HRCR	−0.01	0.32**	−0.07*	−0.02	−0.11***	−0.07**	0.03	−0.06	−0.11***	0.07	−0.01	−0.06
	(0.04)	(0.13)	(0.04)	(0.21)	(0.03)	(0.03)	(0.02)	(0.12)	(0.04)	(0.06)	(0.03)	(0.17)
Doublecrop	0.53*	−4.45*	−0.27	0.30	−0.62*	−5.40***	0.87**	−0.39	−0.20	−7.75***	0.55**	−0.13
	(0.29)	(2.45)	(0.54)	(0.72)	(0.31)	(1.06)	(0.34)	(0.23)	(0.36)	(1.83)	(0.26)	(0.50)
Agrlabor	−0.27	0.23*	−0.11	−0.33	0.57**	0.15**	0.46**	0.15	0.34	0.29***	0.32	−0.01
	(0.21)	(0.12)	(0.32)	(1.17)	(0.27)	(0.06)	(0.17)	(0.64)	(0.28)	(0.10)	(0.22)	(1.01)
Fert	0.03	0.78***	0.23**	0.04	0.12	0.22*	0.13**	0.42***	0.14	0.59***	0.22***	0.39*
	(0.09)	(0.25)	(0.08)	(0.34)	(0.08)	(0.12)	(0.05)	(0.09)	(0.09)	(0.18)	(0.06)	(0.22)
Irri	−0.44***	−1.24***	−1.31***	−0.29	0.76***	0.82***	1.08***	0.08	0.41***	0.24	0.19	−0.10
	(0.12)	(0.29)	(0.29)	(0.39)	(0.11)	(0.16)	(0.17)	(0.14)	(0.14)	(0.21)	(0.19)	(0.28)
Disarea	−0.03	−0.37***	−0.10**	−0.07	−0.01	0.04	0.02	0.04	−0.03	−0.13**	−0.03**	0.01
	(0.03)	(0.08)	(0.04)	(0.12)	(0.02)	(0.03)	(0.02)	(0.07)	(0.02)	(0.05)	(0.02)	(0.11)
_cons	0.40*	−4.42	0.15	−0.64	0.49*	−6.39***	−0.60	0.72*	0.68**	−8.98***	−0.27	0.26
	(0.21)	(3.27)	(0.85)	(1.14)	(0.25)	(1.46)	(0.49)	(0.37)	(0.31)	(2.47)	(0.50)	(0.78)
No. of observations	28	28	28	28	28	28	28	28	28	28	28	28
Marginal effect of HR	0.154***	−0.079	0.278***	0.050	−0.022	−0.026	−0.020	−0.471***	0.084**	−0.057	0.131***	−0.347

The results are based on Equation (10) using the OLS regression.
***, **, *Refers to the significance level of 1%, 5%, and 10%, respectively.
Heteroscedasticity-robust standard errors are in parentheses.
Marginal effects are computed by coefficients of HR and HRCR and the mean of CR in each province.

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TABLE 5 Interaction effects of hybrid rice variety adoption at province level by pairs using the OLS model.

Dependent variables	Provinces	Provinces											
		Hunan	Jiangxi	Guangdong	Sichuan	Anhui	Fujian	Guangxi	Guizhou	Hubei	Jiangsu	Yunnan	Zhejiang
Yield	Hunan	–	0.039	−0.402***	0.181***	0.233	0.027	−0.046	−0.100	0.051	0.022	0.152	0.108
	Jiangxi	0.019	–	−0.331***	−0.054	0.257	0.062	−0.137	0.045	−0.035	0.078	0.180	0.066
	Guangdong	−0.096	0.224**	–	0.681***	0.342	0.110	0.674	−0.034	0.890*	0.697*	−0.025	0.294
	Sichuan	0.049	0.239***	−0.262**	–	0.174	0.067	0.137	0.055	0.016	0.088	0.179	0.124
Area	Hunan	–	0.004	−0.170***	−0.035*	0.041	−0.066**	−0.100***	−0.009**	0.017	−0.045	0.003	0.040
	Jiangxi	0.132	–	−0.181***	−0.047	−0.009	−0.019	−0.092***	−0.010	0.022*	−0.138***	0.009*	−0.003
	Guangdong	0.274**	0.009	–	−0.003	0.111	−0.000	−0.167	−0.022	−0.058	−0.179**	−0.009	−0.009
	Sichuan	0.160***	−0.025	−0.205***	–	−0.001	−0.007	−0.100***	−0.018**	0.005	−0.104***	−0.002	−0.002
Production	Hunan	–	0.027	−0.331***	0.040	0.106	−0.052**	−0.105**	−0.018	0.048	−0.051	0.028	0.063
	Jiangxi	0.137**	–	−0.301***	−0.084	0.076	−0.005	−0.132***	−0.004	0.025	−0.147	0.038	−0.008
	Guangdong	0.211	0.130	–	0.308***	0.220	0.025	0.104	−0.018	0.291	0.033	−0.016	0.060
	Sichuan	0.185***	0.105***	−0.278***	–	0.060	0.005	−0.035	−0.010	0.021	−0.101	0.026	0.009

The results are based on Equation (11) using the OLS regression and show the interaction between two provinces by pair grouping.
The coefficients indicate the average effect of the number of hybrid rice varieties on rice production including yield, area, and production.
The regression results are omitted in the publication and will be provided upon request.
Heteroscedasticity-robust standard errors are applied.
***, **, *Refers to the significance level of 1%, 5%, and 10%, respectively.

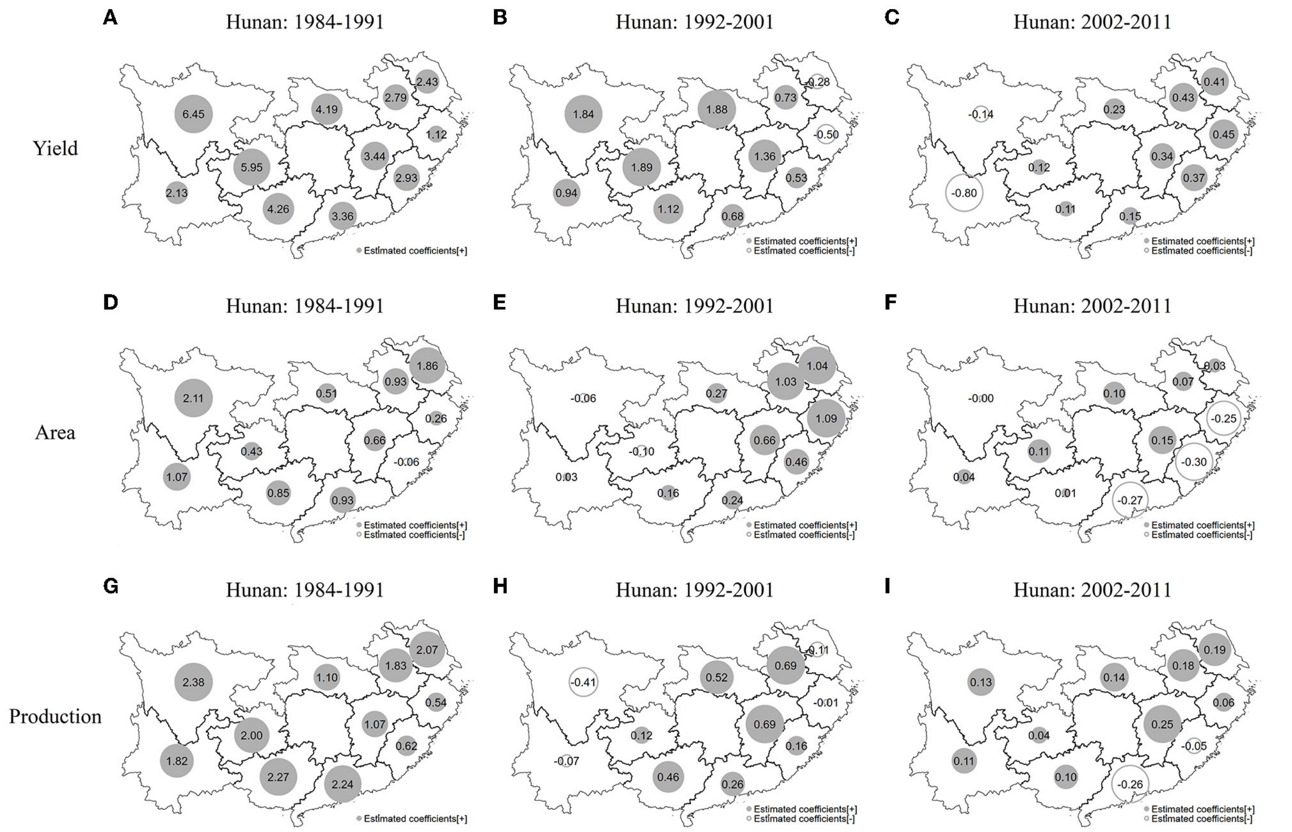

FIGURE 2
Spatio-temporal distribution of regression coefficients of hybrid rice adoption in the Hunan province using the GTWR model from 1984 to 2011. **(A–C)** Represent the spatial distribution of regression coefficients with rice yield from 1984 to 1991, from 1992 to 2001, and from 2002 to 2011, respectively; **(D–F)** represent the spatial distribution of regression coefficients with rice area from 1984 to 1991, from 1992 to 2001, and from 2002 to 2011, respectively; **(G–I)** represent the spatial distribution of regression coefficients with rice production from 1984 to 1991, from 1992 to 2001, and from 2002 to 2011, respectively. The values in the circles are the estimated coefficients of the number of hybrid rice varieties. The circles with shadow mean the estimated effects are positive, while those with blank mean negative.

the development of hybrid rice variety adoption gradually moved from west to east. Between 2002 and 2011, Zhejiang province's rice yield was most affected by Hunan province, although the estimated coefficient in Figure 2C was only 0.45 and much lower than in earlier periods. Regarding the changes in rice yield, the development of hybrid rice variety adoption in Hunan province had a bigger influence on rice production in the provinces located in southern China, particularly in developed areas.

The trend of the spatio-temporal effect of hybrid rice variety adoption on rice area is similar to that of rice yield (Figures 2D–F). However, the extent of changes over time tended to be facilitated. This to some extent shows how hybrid rice adoption has affected change in rice-cultivating areas over time. In the 1980's, the development of hybrid rice variety adoption in Hunan province had a bigger positive impact on provinces farther away, such as Sichuan, Jiangsu, and Yunnan provinces. In the 1990's, the areas that affected other areas more shifted to provinces with better economic development or main rice-producing areas like Jiangxi and Anhui provinces. In the 2000's, the effects changed substantially as many estimated coefficients were negative although the values were much smaller compared to those in the 1980's. For example, the rice area in Sichuan province was positively affected by hybrid rice variety adoption in Hunan province in the 1980's with an estimated coefficient of 2.11 (Figure 2D) at the highest level, but thereafter, the effect diminished and turned negative which was insignificant.

Overall, the development of hybrid rice variety adoption in Hunan province substantially contributed to the increase in rice production in China as the estimated coefficients on rice production across provinces have mostly been positive (Figures 2G–I). However, the contribution has shrunk over time as the values of estimated coefficients have become smaller. However, the trend of effects on rice production across different provinces has been different compared to those of rice yield and rice area. In general, most effects of hybrid rice variety adoption on rice production followed the laws of geography and the effects were usually bigger for provinces that were closer to Hunan province.

4.3.2. Sichuan province

Sichuan is one of the main rice seed production areas and one of the first provinces to widely adopt hybrid rice varieties. The development of hybrid rice varieties in Sichuan

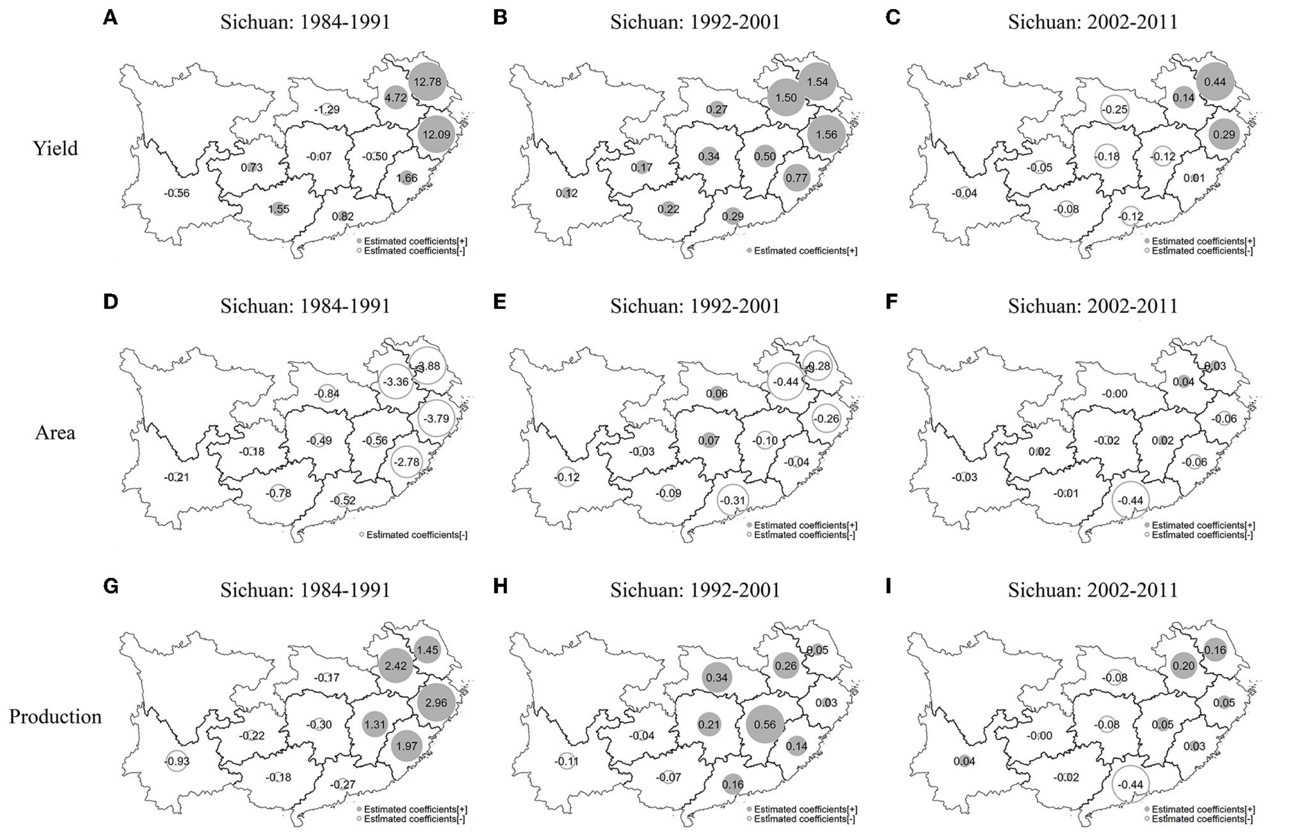

FIGURE 3
Spatio-temporal distribution of regression coefficients of hybrid rice adoption in Sichuan province using the GTWR model from 1984 to 2011. **(A–C)** Represent the spatial distribution of regression coefficients with rice yield from 1984 to 1991, from 1992 to 2001, and from 2002 to 2011, respectively; **(D–F)** represent the spatial distribution of regression coefficients with rice area from 1984 to 1991, from 1992 to 2001, and from 2002 to 2011, respectively; **(G–I)** represent the spatial distribution of regression coefficients with rice production from 1984 to 1991, from 1992 to 2001, and from 2002 to 2011, respectively. The values in the circles are the estimated coefficients of the number of hybrid rice varieties. The circles with shadow mean the estimated effects are positive, while those with blank mean negative.

province enabled the provision of quality seeds to other rice-producing areas (Jing et al., 2013). Thus, taking the number of varieties adopted by farmers as a proxy for agricultural technology development, Sichuan province was expected to contribute to rice production in other provinces, especially the main rice-producing areas.

In general, the effect of hybrid rice variety adoption in Sichuan province has reduced over time (Figure 3). Our results showed that hybrid rice adoption in Sichuan province positively contributed to the rice yield in most rice production provinces in the 1980's, but had a bigger impact on provinces farther from Sichuan, particularly the provinces in eastern China including Jiangsu and Zhejiang (Figures 3A–C). Compared to the effect's distribution, the variation of estimated coefficients in Sichuan province in the 1980's, ranging from negative to the value of 12.78 in Figure 3A, was much bigger than that in Hunan province. In the 1990's, the development of hybrid rice variety adoption in Sichuan had positive effects on the rice yield in all rice-producing provinces although most estimated coefficients were smaller than 1 (Figure 3B). In the 2000's, only Zhejiang, Jiangsu, and Anhui provinces remained positively affected with low estimated coefficient values of <0.5 (Figure 3C). Overall, the effects of hybrid rice adoption in Sichuan province on the rice area across different provinces have been minimal in the last few decades.

The development of hybrid rice variety adoption in Sichuan province contributed considerably to rice production in the 1980's and 1990's, as nearly half of the estimated coefficients were positive (Figures 3G–I). The effects increased with distance, defying the first law of geography. The adoption of hybrid rice varieties in Sichuan province had a significant effect on rice production in Anhui and Jiangxi provinces in the 1990's and 2000's. The development of hybrid rice varieties in Sichuan province had a negative effect on rice production in the neighboring provinces, including Guangxi and Guizhou provinces, which might have been caused by the compensation effect among different provinces (Figures 3D–I).

Our results were not always consistent with the law of geography, in that the degree of influence diminished with distance. There might be three reasons for this. First, the collaborative breeding technology program among scientists and institutions

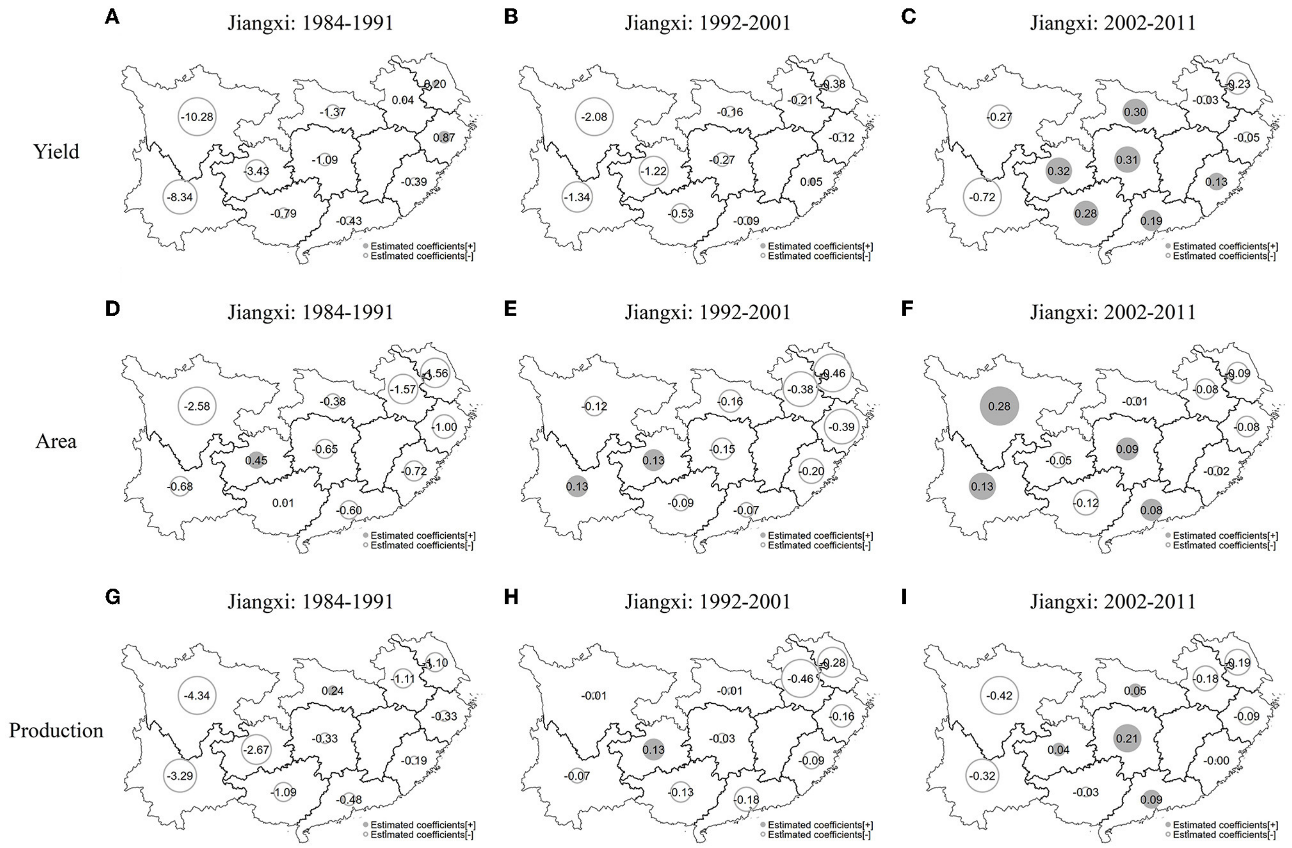

FIGURE 4
Spatio-temporal distribution of regression coefficients of hybrid rice adoption in Jiangxi province using the GTWR model from 1984 to 2011. **(A–C)** Represent the spatial distribution of regression coefficients with rice yield from 1984 to 1991, from 1992 to 2001, and from 2002 to 2011, respectively; **(D–F)** represent the spatial distribution of regression coefficients with rice area from 1984 to 1991, from 1992 to 2001, and from 2002 to 2011, respectively; **(G–I)** represent the spatial distribution of regression coefficients with rice production from 1984 to 1991, from 1992 to 2001, and from 2002 to 2011, respectively. The values in the circles are the estimated coefficients of the number of hybrid rice varieties. The circles with shadow mean the estimated effects are positive, while those with blank mean negative.

was usually attributed to the social network and research interest instead of distance. The cooperation among the breeders and agronomists potentially facilitated the exchange of research materials and the development of hybrid rice varieties. Second, the development of seed companies may have affected the diffusion of hybrid rice varieties substantially as commercialization was essential for hybrid rice variety adoption. Third, local government support and relevant policy could have equally had a biased influence. Further study would be necessary to consider the three factors and help investigate how the spatial effects of hybrid rice variety adoption across provinces are affected.

4.3.3. Jiangxi and Guangdong provinces

Jiangxi province is an important rice-producing area in China, accounting for ∼10% of the rice area and rice production. The rice-cultivating area in Jiangxi province increased in the last few decades, while in most other provinces, it declined. Double rice cropping area was promoted in 2020 (Xu et al., 2022). Compared to Hunan province, Jiangxi province had much less effect on other rice-producing areas (Figure 4). This result was different from previous ones based on the regression using Equation (10) by pair grouping regression (Table 5). Jiangxi province might have been the neighbor that benefited more from the spillover effect of the development of hybrid rice technology in Hunan province instead of being a contributor.

In contrast to the effects of hybrid rice development in Hunan province, the increased adoption of hybrid rice varieties in Jiangxi province had a negative effect on rice yields in the 1980's and 1990's in other provinces (Figures 4A, B). In the 2000's, the development of hybrid rice varieties in Jiangxi province started to have a positive impact on rice yields in Hunan, Hubei, Guizhou, Guangxi, Guangdong, and Fujian provinces (Figure 4C). The effects on the provinces including Hunan, Hubei, and Guizhou provinces located closer to Jiangxi with a lower economic development level were larger, while the effects on the rice area caused by hybrid rice variety adoption in Jiangxi province were different from that on rice yields (Figures 4D–F). The variation may have been caused by the local development of rice production, which requires further study. The results also revealed the positive effects of hybrid rice variety adoption in Jiangxi province in the 2000's (Figures 4G–I); however, it is unlikely that such effects could be attributed to hybrid rice technology that has been developed for over 20 years and farmers have become familiar with the hybrid

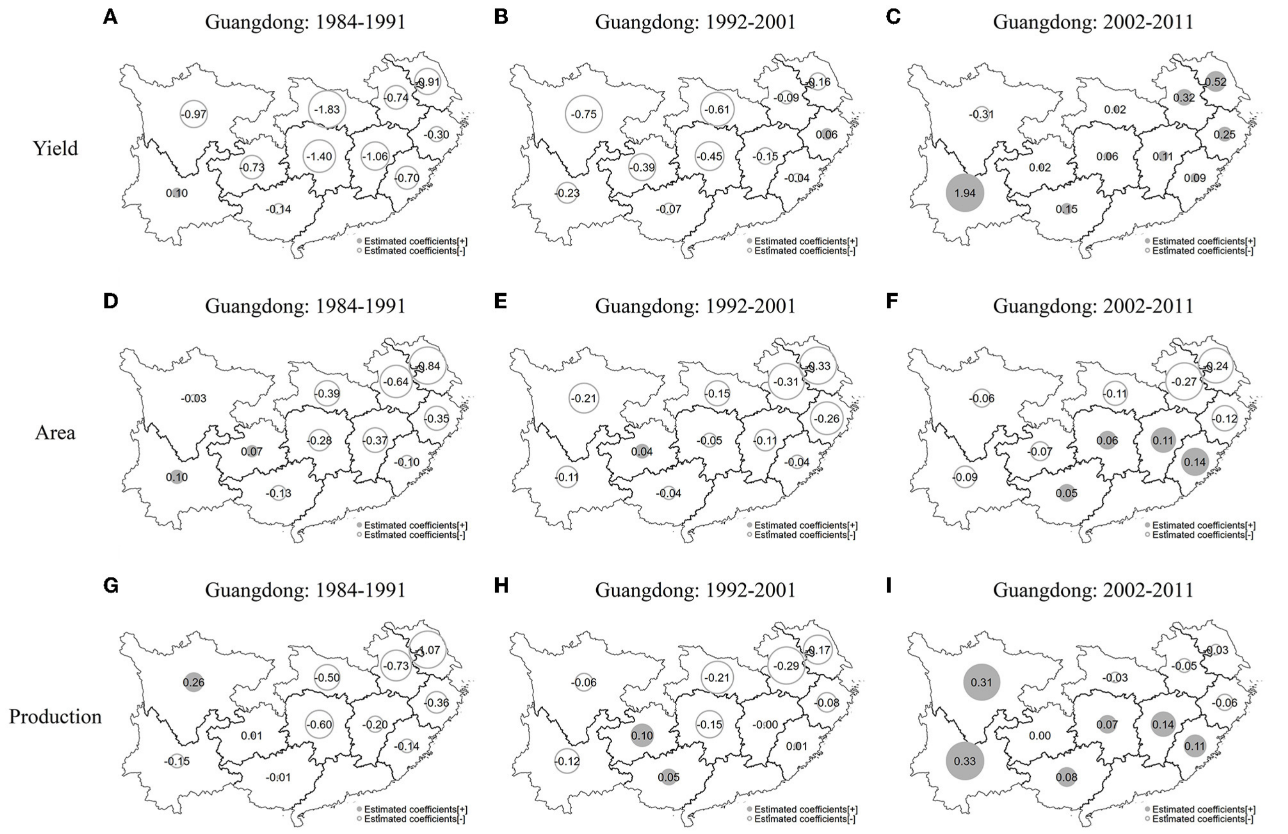

FIGURE 5
Spatio-temporal distribution of regression coefficients of hybrid rice adoption in Guangdong province using the GTWR model from 1984 to 2011. **(A–C)** Represent the spatial distribution of regression coefficients with rice yield from 1984 to 1991, from 1992 to 2001, and from 2002 to 2011, respectively; **(D–F)** represent the spatial distribution of regression coefficients with rice area from 1984 to 1991, from 1992 to 2001, and from 2002 to 2011, respectively; **(G–I)** represent the spatial distribution of regression coefficients with rice production from 1984 to 1991, from 1992 to 2001, and from 2002 to 2011, respectively. The values in the circles are the estimated coefficients of the number of hybrid rice varieties. The circles with shadow mean the estimated effects are positive, while those with blank mean negative.

rice varieties. The possible contribution of Jiangxi province might be the base for new and improved hybrid rice variety adoption due to its large-scale double-cropping rice area. A large number of hybrid rice varieties adopted in Jiangxi province could have facilitated the development of seed companies and information exchange among farmers. Therefore, the increase in the number of hybrid rice varieties in Jiangxi province had a significant positive effect on both rice yield in Hunan and Guangdong provinces in the 2000's (Figure 4I). On the other hand, the development of hybrid rice production in Jiangxi may have also contributed to the reduction of rice production in other areas in the context of urbanization and reduced the availability of agricultural land for rice farming.

Of the selected four provinces, the development of hybrid rice production in Guangdong province witnessed slow progress in terms of the amount of hybrid rice variety adoption and share of hybrid rice area (Figure 5). Although hybrid rice variety adoption in the Guangdong province has had an insignificant effect on the rice areas in developing areas such as Jiangxi province, it has had a positive effect on the rice yield in developed areas such as Jiangsu province (Table 5).

4.4. Robust analysis

As mentioned earlier, the GTWR model was applied to identify both the spatial and temporal effects of technology adoption compared to OLS and the GWR model. We compared the results of different methods. First, the results from OLS, GWR, and GTWR regression[2] were mostly consistent, which showed that the results from the GTWR regression were reliable and robust. The results from ANOVA[3] showed that the residual sum of squares of the GTWR model was lower than that of the GWR model, which indicated that the GTWR model was an appropriate method (Brunsdon et al., 1999). Second, the effects of technology adoption may be biased without considering the temporal effects. The coefficients of GWR regression present the average value of spatial effects across provinces. The impacts of hybrid rice adoption in Hunan, Sichuan, and Anhui provinces on rice yield were both negative in the OLS and GWR regressions but were positive in the

2 The results of OLS, GWR, and GTWR based on Equations (12–14) are shown in Supplementary Tables 2–4.

3 The results of ANOVA tests are shown in Supplementary Table 1.

GTWR regression. At the beginning of the hybrid rice adoption, a demonstration effect played a dominant role which resulted in the extension of the hybrid rice cultivation areas. Subsequently, as most regions began adopting large-scale hybrid rice production, there was competition among the main rice-producing areas and a crowding effect gradually affected the distribution of rice production given the total amount of rice demand. From the perspective of technology development, rice yield potential has recently reached its ceiling (Cassman et al., 2003; Licker et al., 2010; Neumann et al., 2010; Van Wart et al., 2013). The yield advantage of hybrid rice was different in the 2010's compared to the 1980's when the hybrid rice variety achieved both significant yield gain and the potential to be improved continuously. Simultaneously, the yield potential of conventional rice has also increased and the average yield of conventional rice reached 5.8 t/ha in 2009 (Deng, 2012). Meanwhile, consumers' increasing demand for particular rice qualities significantly affected farmers' hybrid rice production due to increases in economic growth and income. The results showed that extensive adoption of hybrid rice varieties in the country happened in the 1990's, which promoted rice yield and increased rice production associated with increasing agricultural inputs. The further extension of hybrid rice in the 2000's was stagnant and declined in some provinces such as Jiangsu, Jiangxi, and Guangxi. Without considering the temporal effects, the impacts of hybrid rice adoption could be biased because the effects of agricultural technology adoption have varied over time.

5. Discussion

Taking the number of mega hybrid rice varieties adopted by farmers as a measurement of new technology adoption, this study provided a detailed analysis of the dynamic changes in hybrid rice adoption and its impact on rice production in China. Hunan, Sichuan, Jiangxi, and Guangdong provinces, which first promoted and supported large-scale commercial hybrid rice production[4] (Ma and Yuan, 2015; Xie and Zhang, 2018) were taken as examples to estimate the effects of hybrid rice adoption and interaction of variety adoption across regions. The number of mega hybrid rice varieties in the four provinces accounted for 47% of the total hybrid rice varieties for large-scale commercial production.

The number of hybrid rice varieties adopted for large-scale production, to some extent, reflected the level of commercialization of hybrid rice and indicated the advantage of yield gain due to the heterosis advantage. The results confirmed the positive effect of hybrid rice adoption on national rice yield and production. In addition, widespread adoption reduced rice-cultivating areas substantially, which is consistent with the findings of previous studies (Huang et al., 2021).

The cropping pattern of rice production changed substantially due to the rapid expansion of hybrid rice production. In developed provinces like Guangdong, a net importer of rice, the adoption of hybrid rice satisfied its food security in the early stages, and later on, rice area and labor saved in hybrid rice production were used for various other income-generating activities such as cash crops or non-farm activities (FAORAP, 2014; Hu et al., 2022). In contrast, the widespread adoption of hybrid rice varieties increased the rice-cultivating area and continuous increases in rice production in Hunan, Jiangxi, and Sichuan provinces for decades. This indicated the advantages of rice production across the main rice-producing areas, i.e., the larger the number of hybrid rice varieties, the better the rice production in the developing provinces and economies of scale. Undoubtedly, other socioeconomic factors, such as the development of non-agricultural sectors and climatic conditions have contributed significantly to the change in rice cropping patterns (Pingali, 2012; Hu et al., 2022), which require further study to identify the complex effects of different factors impacting rice cultivation.

The spatial effect of hybrid rice adoption on rice production was identified in the study. Being the center of hybrid rice technology development, the effects of the rapid adoption of hybrid rice in Hunan province on rice production trends in Guangdong, Sichuan, and Jiangxi provinces varied. Previous studies have established the spillover effects of agricultural technology development (Hu et al., 2022), and similarly, the province with rapid extension and adoption of hybrid rice varieties had a positive effect on its neighboring provinces. With the increasing number of hybrid rice varieties adopted in Hunan province, rice production in adjacent Jiangxi province was affected more than in other provinces. This is consistent with the laws of geography (Tobler, 1970).

Large-scale commercial hybrid rice production also positively encouraged the participation of the private sector and seed companies (Cheng et al., 2007; Pingali, 2012). In the early 1980's, hybrid rice varieties were mostly extended and promoted by the government when seed companies had just started (Lin, 1991a; Singh et al., 2018). More seed companies were established and encouraged by the returns in seed production (Huang et al., 2002). By 2011, over 1,250 hybrid rice varieties were being farmed on a large scale. Although the studies on hybrid rice breeding and management technology are collaborative, both spillover and crowding effects were identified in the analysis influencing rice yield, rice-cultivating area, and rice production. The two effects from a given province could happen simultaneously and affect the target province differently. Further studies are imperative to determine how the different effects interact with each other in any given province. In addition, the status and development of seed companies involved in hybrid rice technology were not covered in our study due to data limitations. A study focused on the impact of seed companies on rice cultivation and cropping choices and patterns might be helpful for a better understanding of the number of varieties distributed across different areas. Furthermore, climate change should be included in future analyses since it has affected the center of rice production and the adoption of rice varieties in China (Huang et al., 2021), which may also influence the effect of hybrid rice adoption on rice production. Overall, our results demonstrate the variations in hybrid rice adoption and its spatial effect on rice production in China, which can be used as a reference to monitor and evaluate the effects of new technology adoption in developing

4 Although the first rice variety named Nanyou no.2 was officially released in Guangxi province, we did not take Guangxi province as an individual case considering the importance of rice production and technology development of rice varieties. The rice area and production in Guangxi province accounted for 8.3 and 7.1% in 1982 and 6.6 and 5.2% in 2011, which was lower than that in Guangdong province.

countries and design agricultural extension strategies for the long term to ensure food security. However, further study is necessary to identify the mechanism of technology diffusion in the complex context of economic development and climate change for a better strategy and design.

There are also several limitations in this study. First, the data used in the analysis is limited to secondary data. The estimation might be influenced by the application of proxy variables. For instance, irrigation is important for rice production, while irrigated rice area is not available in the secondary data and has been computed based on the share of the rice area within the arable land area. Although it suggests, to some extent, the different levels of irrigation in rice farming across provinces, the possible gap between computation and the real situation may influence the estimation. Second, we attempted to identify the important factors impacting rice farming in different provinces. A better measurement of the complex environment associated with the ecological system would be desirable. Third, the results of the econometric regression may be affected by omitted variables, such as seed commercialization and industry development. The seed industry and technology extension service are both important for local farmers to access improved rice variety adoption, especially for farmers who grow hybrid rice as they have to buy seeds every year. The lack of specific information on the seed market, including the number of seed companies, the amount and value of hybrid rice seed production, and relevant policies may limit the application of results. Finally, the small sample size that was applied in the analysis at the provincial level to identify the effects of hybrid rice adoption within a specific province would raise concerns. The dataset with longer period data may be needed to produce more reliable results.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

The original work of formal analysis and original draft writing of methodology was performed by QW. The literature review, draft writing of results, revision of analysis, and methodology were contributed by BB. The conceptualization, introduction, and conclusion as well as the manuscript draft and editing were undertaken by HW. All authors have read and agreed to the published version of the manuscript.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fsufs.2023.1071234/full#supplementary-material

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The adoption and impacts of improved parboiling technology for rice value chain upgrading on the livelihood of women rice parboilers in Benin

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Food insecurity and child malnutrition remain persistent problems in sub-Saharan Africa. Rice is a staple food for more than half of the world's population. However, white rice is poor in micronutrients and records higher glycemic values compared to parboiled rice. An improved parboiling system called "Grain quality enhancer, Energy-efficient and durable Material" (GEM in short) allows the processing of quality rice with better physical and nutritional properties compared to traditional systems. This paper assessed the drivers and impact of the adoption of the GEM system on women's livelihoods. A total of 822 rice women parboilers were randomly sampled and interviewed in Benin, in regions where the GEM system was introduced. We employed the endogenous switching regression model (ESR) to assess the impact of the GEM system. We found evidence that adoption of the GEM system increased women parboilers' rice output rate (dehulling return), income and food security and reduced poverty. The impact of the GEM system is estimated at 14.38 kg of milled rice per 100kg of paddy (21.46%), equivalent to US$ 7.25 of additional income (17.77%). A significantly lower poverty rate of 26% was found among households due to the adoption of the GEM system. These results are supported by women's perceptions that the output rate, better nutritional value and reduction of broken rice during dehulling are major advantages of the improved parboiling system. Policy actions such as training of local fabricators and credit options are required for out-scaling and sustainability of the improved parboiling system.

KEYWORDS
quality of rice, improved parboiling system, endogenous treatment effects model, impact, Africa

1. Introduction

West Africa consumes more rice than any part of sub-Saharan Africa (SSA), as regional demand has continued to grow at almost 6% annually, driven by the growing population, changing consumption habits and urbanization (Arouna et al., 2021). However, local production has not kept pace with the increase in demand, and the gap is being filled through the importation of rice from Asia, whose characteristics are preferred by consumers (Demont et al., 2013). The low quality of local rice is mainly due to poor postharvest handling (Zohoun et al., 2018). Postharvest activities are of great importance in terms of value addition, the creation of employment opportunities, women's livelihood improvement and the reduction of food losses. Rice parboiling which is the hydrothermal treatment of paddy (rough rice) before dehulling and polishing has also been explored as a strategy to improve the physicochemical and nutritional quality of rice including its digestibility (Ndindeng et al., 2022). The most noticeable advantages of rice parboiling to the processors are increased dehulling return, higher head rice yields and longer storage shelf-life (Etoa et al., 2016; Ndindeng et al., 2021a). As in most countries in SSA, women parboilers predominantly use traditional practices of parboiling rice with low capacity (Fofana et al., 2011) and poor milled rice quality (Houssou and Amonsou, 2004). As a result, consumers prefer and are willing to pay higher prices for imported rice at the expense of parboiled rice produced using traditional methods and equipment (Houssou et al., 2013; Ndindeng et al., 2021b). Therefore, rice parboiling proves to be an important and strategic solution to improve the competitiveness of local rice (Fofana et al., 2011). To upgrade parboiled rice, an improved rice parboiling system "Grain quality enhancer, Energy-efficient, and durable Material" (GEM) with high capacity was recently introduced in West Africa (Ndindeng et al., 2015). The GEM equipment has a high capacity (up to 1,000 kg per day) compared to only 50–100 kg of the capacity of traditional equipment, reducing labor input and the quantity of firewood used. This helps slow deforestation and reduce the effects of climate change. The improved method also uses steam to parboil rice compared to traditional technology (Zohoun et al., 2018).

The GEM system is an improved model based on prototypes from the Institute of Agricultural Research for Development (Cameroon), the Food Research Institute (Ghana), and the Institut National des Recherches Agricoles du Bénin (Benin). The GEM system was introduced in Benin (in the Collines and Alibori departments) in 2015.

The technical performance of the GEM system was tested through several studies (Ndindeng et al., 2015). However, no economic study has been carried out to evaluate the impact of this new parboiling device. Previous studies have focused on the technical performance of the improved parboiling system (Houssou and Ayernor, 2002; Ndindeng et al., 2015) and the determinants of its adoption (Dandedjrohoun et al., 2012). Technical analysis focused on the characteristics of the equipment and the advantages of the GEM system to improve the quality of rice such as physicochemical and cooking properties of the parboiled rice (Ndindeng et al., 2015). In addition, technical analysis was conducted in an experiment under control. Results showed that for instance percent impurities and heat-damaged grains were lower for rice produced using the GEM system. However, no study was published to analyze the effect of the improvement of rice quality by the GEM system on the income and the livelihood of women rice parboilers. This study aim to quantify the impact of the improved GEM system for rice parboiling on the livelihood of women rice parboilers in Benin. The study addressed two research questions: can the GEM system improve rice output rate (dehulling return) of parboiled rice? What is the quantitative impact of the GEM system on income, food security and reduced poverty? By responding these questions, the contribution of this study to the literature is twofold. First, the study provided the assessment of the impact of GEM system on both income, food security and poverty reduction among women rice parboilers. Second, although there are several studies on impact of technologies in the rice value chain, Mishra et al. (2022) recently showed in their review that impact assessment of rice postharvest technologies in Africa are scanty. This study fill that gap and help providing recommendations to policy makers and extension agents on how to scale the GEM technology to improve the livelihood of women.

The rest of the paper is structured as follows. We describe the GEM system in Section "Description and dissemination of the improved GEM parboiling system in Africa" and discuss the methodology in Section "Methodology". Next, we present and discuss the results in Sections "Results" and "Discussions", respectively. Finally, we conclude the study and discuss its policy implications in Section "Conclusion and policy implications".

2. Description and dissemination of the improved GEM parboiling system in Africa

2.1. Description of the improved GEM parboiling system

GEM parboiling system is an improved parboiling technology that combines the use of a uniform steam parboiler and an improved parboiling stove (Ndindeng et al., 2015). The GEM parboiling system is not only about the equipment but also the process. The GEM parboiling system is scaled as a rice parboiling plant (complex). The main components of the complex are the parboilers (steaming tank and baskets), soaking vessels, stoves, laborsaving device, hot water siphoning system, drying surfaces and a shade that accommodates the equipment. Out-scaling is targeting mainly small processors (< 50 kg/batch; 600–800 kg/week) and medium processors (> 50–100 kg/batch; > 800 kg/week). For small-scale processors, the 20–50 kg GEM parboilers, one single 300–400 kg soaking vessel, a manual water pump and a rotational hoist are used. For medium-scale producers, the 60–100 kg GEM parboilers, several 300–400 kg soaking vessels, a manual water pump and a rail chain hoist are used. Internal and external views of the rice parboiling complex showing innovative equipment and sun-drying surfaces and are well described in the literature[1] (Ndindeng et al., 2015).

2.2. Dissemination of the improved GEM parboiling system in Africa

Rice parboiling is the hydrothermal treatment of rice before dehulling and polishing to reduce grain breakages during the dehulling process, preserve nutrients and enhance cooking and eating quality. Due to the low capacity and quality of parboiled rice using the traditional system, the GEM parboiling system was developed in consultation with women processors from the Glazoué Innovation Platform (IP) in Benin to reduce drudgery, the risk of heat burns and exposure to smoke to processors, who are mostly women. The GEM parboiling system can be tailored to medium- (300–1,000 kg) and large-scale (1000–3,000 kg) processors. The cost of the technology depends on the components and the scale of operation. The equipment consists of a stainless steel (Inox 304 L) soaking tank, a stainless steel

1 http://www.ricehub.org/RT/post-harvest/gem-parboiling/out-scaling-the-gem-parboiling-technology

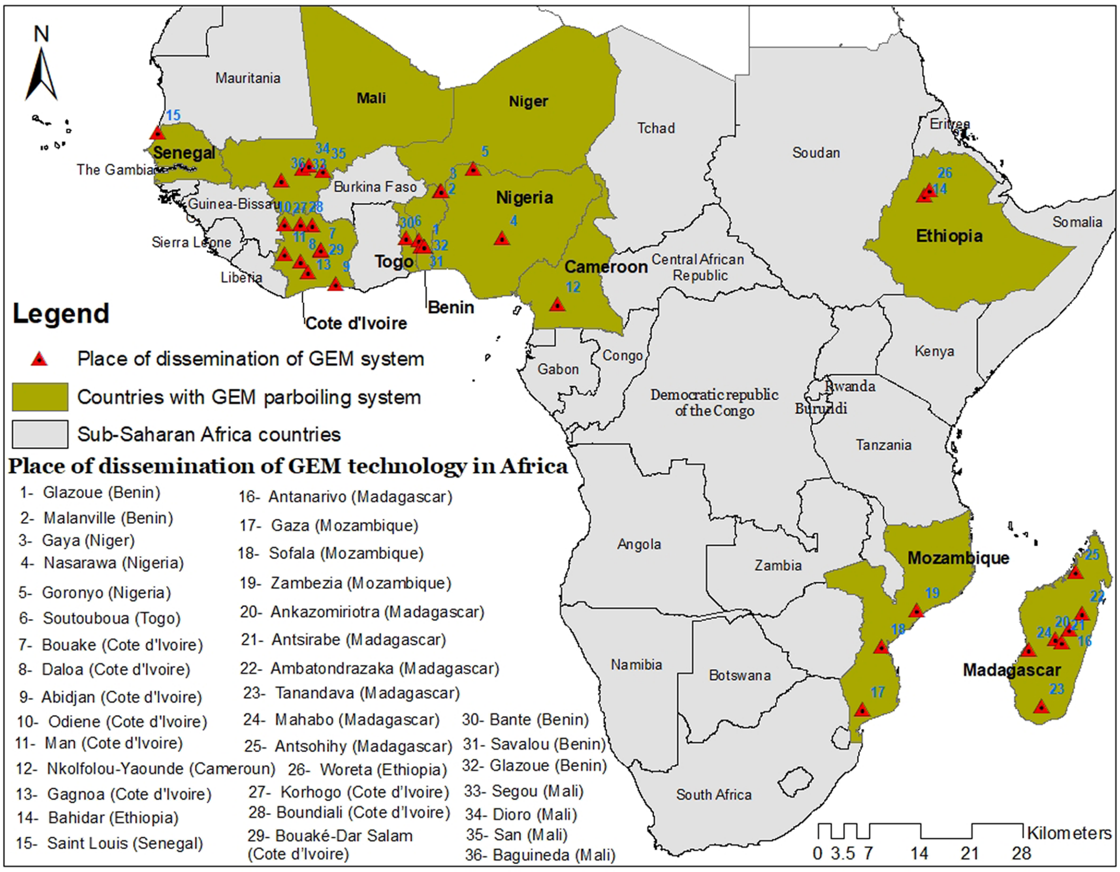

FIGURE 1
Map of Sub-Sharan Africa highlighting the place of dissemination of the GEM system in Africa by AfricaRice.

(Inox 304 L) steaming tank with a stainless steel (Inox 316 L) perforated basket that is placed on a false-bottom in the steaming tank, a hot water pump, a rail and hoist system and an improved rocket stoves constructed with fired bricks and fixed on the ground (Ndindeng et al., 2015). The system is installed under a parboiling shade with a cemented surface so that grains that drop during the parboiling process can be recovered – reduction of quantitative loss (Ndindeng et al., 2021a). Close to the parboiling shade is an improved paddy sun drying area composed of a raised concrete surface with tarpaulins places on it and fenced.

The GEM system is not only about the equipment but the process as well. The installation of the system is accompanied with training of parboilers who are predominantly women on the use of the system to produce quality parboiled. The users are trained on how to select to the most suitable variety and paddy for parboiling – varieties that are slender in shape, rough rice that is neither damaged by disease nor de-husked during threshing. They are also thought on how to clean the rice by winnowing and washing to remove all sorts of impurities, soaking at the right initial temperature (85°C for most varieties and for rough rice that is more than 3 months old), steaming time (20–25 min) and finally on drying regimes and dehulling systems that provide the best results. It is worth pointing out that parboilers using traditional equipment and methods do not consider the above-mentioned points.

The GEM system has been disseminated in many countries in Africa. In the first stage of the dissemination of the GEM system in Africa, training of a dozen agricultural equipment manufacturers was conducted in each country. Women parboilers from the IP in each country were trained in the use and method of rice parboiling with the GEM system. As of January 2022, the GEM system was introduced in a total of 36 areas in Africa (11 African countries): 23 areas in West Africa (Glazoue, Bante, Savalou, Glazoue, and Malanville in Benin; Gaya in Niger; Nasarawa and Goronyo in Nigeria; Soutouboua in Togo; Bouake marché de gros, Bouake Dar Salam, Abidjan, Odiene, Man, Gagnoa, Korhogo, Boundiali, and Daloa in Cote d'Ivoire; Segou, Dioro, San and Baguineda in Mali; and Saint Louis in Senegal); one area in Centrale Africa (Nkolfolou-Yaounde in Cameroon) and 12 areas in East Africa (Bahidar and Woreta in Ethiopia; Antanarivo, Antsirabe, Ambatondrazaka, Ankazomiriotra, Tanandava, Mahabo and Antsohihy in Madagascar; and Gaza, Sofala and Zambezia in Mozambique). Figure 1 highlights all 36 areas of dissemination of the GEM parboiling system in Africa.

3. Methodology

3.1. Estimation method

The impact of the GEM parboiling system on different outcomes was analyzed using the endogenous switching regression model to account for selection bias due to both observable and unobservable factors.

Endogenous switching regression can capture selection bias and the endogeneity problem and is able to provide results under different counterfactual states of adoption decisions (Lokshin and Sajaia, 2011; Khonje et al., 2015). ESR has been applied in many empirical studies (Di Falco and Veronesi, 2013; Ngombe et al., 2017). Therefore, this paper uses ESR to estimate the average situation of rice parboilers if they had not adopted the GEM parboiling system.

The adoption of the GEM system is voluntary and involves self-selection. To overcome the induced bias, the population of the treatment group (adoption group) must be similar to the population of the non-adoption group, and only the observed difference is the adoption of the GEM system. Let D_i be a dichotomous variable indicating the adoption status of a woman parboiler, with $D_1 = 1$ if she adopts the GEM system and $D_0 = 0$ otherwise. Suppose Y_{1i} and Y_{0i} are random variables of outcomes when a woman adopts and when she has not adopted, respectively. Indeed, adoption and non-adoption status cannot be observed simultaneously for an individual parboiler. ESR allows us to estimate the counterfactual situation that cannot be observed (Lokshin and Sajaia, 2011; Khonje et al., 2015). The ESR model includes two simultaneous equations and can be expressed as follows:

$$Y_{1i} = \beta_{1i} X_{1i} + \varepsilon_{1i}, \ if \quad D_1 = 1$$

$$Y_{0i} = \beta_{0i} X_{0i} + \varepsilon_{0i}, \ if \quad D_0 = 0$$

For $$D_i = 1 \quad \vartheta_i Z_i + \mu_i > 0$$

For $$D_i = 0 \quad \vartheta_i Z_i + \mu_i \leq 0,$$

where X_{1i} and X_{0i} are the explanatory variables of the adoption/nonadoption, β_{1i} and β_{0i} are the parameter vectors of the model, and $\varepsilon_{0i}, \varepsilon_{1i}$ and $\propto_i$ are the error terms assumed to be normally distributed.

The ESR model allows estimating the expected outcome (income, output rate, food security and poverty status) of the rice parboiler adopter and nonadopter in the different statuses of adoption: the outcome of an adopter who did adopt (a), the expected outcome in the counterfactual hypothetical case (in case of an adopter who did not adopt) (c), the outcome of nonadopters (b), and the expected outcomes of nonadopters if they did adopt (d). The conditional expectations of the outcomes of parboilers in the four cases are defined as follows and summarized in Table 1:

$$E\left(y_{1i} | D_i = 1\right) = \beta_{1i} X_{1i} + \sigma_{1\eta} \lambda_{1i} \quad 1$$

$$E\left(y_{0i} | D_i = 0\right) = \beta_{0i} X_{0i} + \sigma_{0\eta} \lambda_{0i} \quad 2$$

$$E\left(y_{0i} | D_i = 1\right) = \beta_{0i} X_{1i} + \sigma_{0\eta} \lambda_{1i} \quad 3$$

$$E\left(y_{1i} | D_i = 0\right) = \beta_{1i} X_{0i} + \sigma_{1\eta} \lambda_{0i} \quad 4$$

Cases (1, 2) and in the diagonal of Table 2 represent the actual and observed outcomes in the sample. Cases (3, 4) represent the counterfactual outcomes of interest (income, output rate, food security, and poverty status).

Moreover, ESR allows calculating the impact of the treatment on the treated (ATT) as the difference between Cases (1, 3) (Heckman et al., 2001). ATT represents the impact of adoption on the outcome of the parboilers who actually adopted the GEM system and is expressed as follows:

$$\begin{aligned} ATT &= E\left(y_{1i} | D_i = 1\right) - E\left(y_{0i} | D_i = 1\right) \\ &= X_{1i}\left(\beta_{1i} - \beta_{0i}\right) + \lambda_{1i}\left(\sigma_{1\eta} - \sigma_{0\eta}\right) \end{aligned}$$

Similarly, the impact of the treatment on the untreated (ATU) represents the impact that the GEM system would have on nonadopters in case they decide to adopt, and it is estimated as the difference between Cases (2, 4):

$$\begin{aligned} ATU &= E\left(y_{1i} | D_i = 0\right) - E\left(y_{0i} | D_i = 0\right) \\ &= X_{0i}\left(\beta_{1i} - \beta_{0i}\right) + \lambda_{0i}\left(\sigma_{1\eta} - \sigma_{0\eta}\right). \end{aligned}$$

The validity of the results largely depends on the quality and relevance of the instruments. Good instruments should fulfill the exclusion restriction, meaning that instruments should affect the decision to adopt but have no correlation with the outcomes (Abadie, 2003). Contact with extension services and being trained in the GEM system are selected as instrumental variables in this study. The choice of these variables is justified by the fact that contact with extension services and training in agriculture can provide information and knowledge on the GEM system and may affect the decision to adopt this technology. Only women parboilers with information on the GEM system can adopt it. However, awareness and information

TABLE 1 Conditional expectations, treatment effects, and heterogeneity.

Subsamples	Decision status		Treatment effects
	Adopt	Nonadopt	
Adopters	(a) $E\left(y_{1i} \| D_i = 1\right)$	(c) $E\left(y_{0i} \| D_i = 1\right)$	ATT
Nonadopters	(d) $E\left(y_{1i} \| D_i = 0\right)$	(b) $E\left(y_{0i} \| D_i = 0\right)$	ATU

ATT: the average treatment effect on treated; ATU: the average treatment effect on untreated.

TABLE 2 Distribution of rice parboilers surveyed in Benin.

Country	Area	Region	Frequency	Percentage
Benin	North	Malanville	400	48.66
	Centre	Bante	80	9.73
		Dassa	149	18.13
		Glazoue	48	5.84
		Ouesse	23	2.80
		Savalou	105	12.77
		Save	17	2.07
Total			822	100

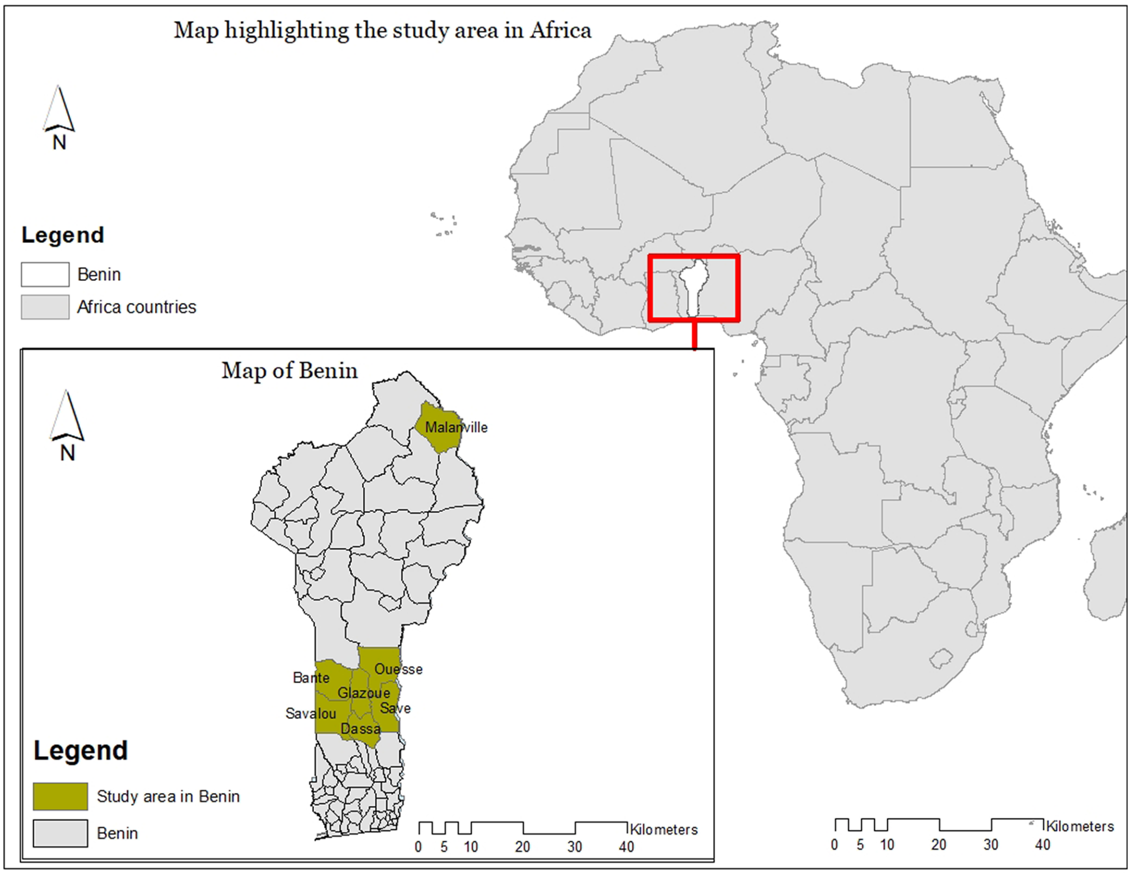

FIGURE 2
Map of Benin highlighting the study area.

cannot directly influence the outcome. In addition, we test the validity of the two instruments. Following Di Falco et al. (2011), we performed a simple falsification test: if a variable is a valid selection instrument, it will affect the technology adoption decision, but it will not affect the outcome variables. To assess the impact of the GEM system, we use the "movestay" command of STATA to estimate the endogenous switching regression model.

3.2. Sampling method and data collection

The study was conducted in seven districts of the Republic of Benin, including Malanville in the northern part of the country, Bantè, Savalou, Dassa-Zounme, Glazoué, Savè, and Ouèssè and the central part of the country (Figure 2). These regions were selected purposively for two main reasons: their major rice production areas are in Benin (Arouna and Aboudou, 2020), and the GEM system was first introduced in these areas through training and demonstration.

A two-stage random sampling technique was used to select the households of the parboilers in the study area. In the first stage, villages were randomly selected from the list of villages where parboiling activities were conducted and from where women were trained in GEM parboiling. The number of villages per district was proportional to the total number of eligible villages per district. From each selected village, the list of all rice-parboiler households was developed, and the women parboilers were randomly selected. The number of women parboilers per village was proportional to the total number of women parboilers in the village. In total, 822 women were randomly selected. This resulted in the number of parboilers to investigate in each village (Table 2).

Data were collected by enumerators selected based on their experience and trained in the use of the CSPro application on tablets. Computerized data collection has avoided many of the biases associated with paper questionnaires, such as errors in recording responses, changing variable values, and recording test responses for numeric variables. Data collection was conducted between January and February 2019. Four main categories of data were collected: socioeconomic and demographic characteristics, type of systems used for rice parboiling, perception of women of different parboiling systems and quantity and price of inputs and outputs in paddy parboiling activity.

3.3. Description of outcome variables and data

The first outcome variable of interest is the output rate. In the context of this study, we defined the output rate (dehulling return) as the quantity of dehulled rice obtained from a bag of 100 kg of paddy rice after parboiling and dehulling. It is expressed in kilograms per

100 kg of paddy. Second, we expressed the impact of adoption of the GEM system on income defined as income per 100 kg of paddy rice parboiled and milled. Income was calculated by multiplying the output rate per 100 kg of paddy by the average unit price of 1 kg of parboiled and milled rice in the data (in US$) (Income = Output rate *Price). To assess the impact of the GEM system on food security, we used two complementary indicators: the food consumption score (FCS) and *per capita* food expenditure. The FCS is a composite indicator developed by the World Food Programme (WFP, 2009), which reflects food availability, access to food and food consumption at the household level. The FCS is, therefore, a good indicator to evaluate the food security of parboiler households. However, the food consumption score may not capture all the actual household food consumption costs. Therefore, we added food consumption expenditure, which includes both the parboilers' own production and purchased food for consumption at the household level. Finally, the poverty line was calculated from the monthly mean adult-equivalent household expenditure (MAHE)[2] of the sample household. Two-thirds of the MAHE for sample households was used as the poverty line for the study. This approach has already been used in several research studies (World Bank, 1996; Amaza et al., 2009; Abass et al., 2017).

Table 3 describes the characteristics of the surveyed women parboiler households. Mean difference tests showed that the hypothesis of no difference between adopters and nonadopters of the GEM system is rejected for most characteristics. These results underscored the presence of selection into adoption, and heterogeneity between adopters and nonadopters must be considered in the impact assessment of the GEM system. Specifically, descriptive statistics showed a difference in the rice output rate between adopters and nonadopters. On average, the overall paddy output rate obtained by a parboiler is approximately 58 kg per 100 kg of paddy rice, with 50.39 kg for nonadopters and 65 kg for adopters. The average income of parboilers is also different based on adoption status. After parboiling and dehulling a bag of 100 kg of paddy, parboiler income is generally approximately US$ 36. The food consumption score and food consumption expenditure were also significantly different between adopters and nonadopters. The poverty headcount ratio is significantly different, at 0.39 and 0.24 for nonadopters and adopters of the GEM system, respectively. This means that 24% of the adopters are poor, while 39% of the nonadopters of the GEM parboiling system are poor. However, this difference between adopters and non-adopters should not be considered as an impact of the GEM system. Indeed, because of heterogeneity between adopters and non-adopters and self-selection into the adoption of the GEM system, other factors apart from adoption of GEM system may explain the difference between the two groups. The ESR method used in this study helps to account for other factors in the estimation of the impact of GEM technology.

The results showed that adopters and nonadopters of the GEM system are also distinguishable in terms of household characteristics. Evidence from Table 3 shows that the mean age of the parboilers was 43 years old, and they were mainly women. This highlights the fact that the stakeholders in parboiling activity in Benin were women. Approximately 93% of respondents were married, a sign of independence and maturity as cultural norms in Benin villages. The mean household size of the sample surveyed is 6 people. Furthermore, approximately 61% of respondents received training on the GEM system, with 96% being adopters and 26% being nonadopters. The fact that 26% of women received the training on the GEM system but they did not adopt can be explained by other factors that also affect the decision of women parboilers to adopt the GEM system. These factors are analyzed in the results section. Approximately 34% of the women parboilers had formal education. Only 8% of the respondents reported that they had recently obtained credit for rice processing. Moreover, 55% of parboilers were engaged in rice parboiling activities as their main occupation, and 36% of parboilers were also rice producers. In addition, all parboilers were members of parboiler associations. Finally, approximately 78% of respondents had contact with agricultural extension agents.

For a robustness check, we tested the properness of the two instruments (contact with extension service and training in agriculture) used. The results showed that contact with extension services and training in agriculture are jointly statistically significant in explaining the adoption of the GEM system but not in the outcomes (Table A1). To further check the robustness of the instruments, we also performed weak instrument and overidentification tests (Staiger et al., 1997). We rejected the null hypothesis that the instruments are weak [$F = 385.16$ ($p = 0.00$)] (Table A1). However, the instruments affected all five outcomes. Furthermore, we performed the overidentification test (Table A1). Therefore, simple falsification, weak instruments and overidentification tests confirm the validity of the two instruments (contact with extension services and training on the GEM) used in this study.

4. Results

We started this section with an analysis of the perception of women parboilers. This is followed by the analysis of drivers of the adoption of the GEM parboiling system. Finally, we present the impact of the adoption of the GEM parboiling system on different outcomes (income, output rate, food security and poverty headcount ratio) of women rice parboilers.

4.1. Perception of rice parboilers on parboiling activity in Benin

4.1.1. General constraints of rice parboiling activities

Rice parboilers in Benin face several processing constraints that contribute to making the local industry noncompetitive. Following an extensive review of the literature and talking to experts in the sector, a list of constraints was identified (Table 4), and parboilers were then asked to rank these constraints based on their experience and operations. The mean rank for each constraint was then calculated, and the rank was determined using Kendall's coefficient of concordance.

2 The living standard of households was measured based on the expenditure of the households. *Per capita* expenditure was derived by dividing the household expenditure with the number of members in the parboilers' household and standardized to adult equivalent based on the equivalency scales of Martin (2017).

TABLE 3 Socioeconomic characteristics of respondents.

Variables	Overall (n=822)	Nonadopters (n=412)	Adopters (n=410)	Mean difference
Outcome variables				
Income for 100 kg of paddy ($USD)	35.94 (7.46)	31.03 (5.12)	40.89 (6.05)	−9.852***
Output rate for 100 kg of paddy (kg)	57.68 (8.26)	50.39 (5.08)	65.02 (1.90)	−14.63***
Food consumption score (unite)	75.63 (14.24)	67.27 (11.84)	84.03 (11.18)	−16.77***
Food consumption expenditure ($USD/Year)	868.59 (427.97)	777.84 (491.13)	959.79 (329.62)	−181.96***
Poverty headcount ratio (%)	0.31 (0.46)	0.39 (0.48)	0.24 (0.43)	0.15***
Household characteristics				
Age of rice parboiler (year)	43.51 (10.01)	44.04 (9.05)	42.98 (10.88)	1.06
=1 if age is ≥40	0.64 (0.47)	0.68 (0.47)	0.60 (0.48)	0.077**
Household size (Number)	6.84 (3.36)	6.30 (3.44)	7.39 (3.19)	−1.09***
Number of children (Number)	2.56 (1.80)	2.17 (1.57)	2.95 (1.93)	−0.78***
=1 if female (%)	0.99 (0.07)	0.99 (0.06)	0.99 (0.06)	0.00
=1 if married (%)	0.93 (0.25)	0.93 (0.26)	0.93 (0.25)	−0.01
=1 if parboiler has a formal education (%)	0.34 (0.47)	0.37 (0.48)	0.30 (0.45)	0.07**
=1 if parboiling is main activity (%)	0.55 (0.49)	0.51 (0.50)	0.59 (0.49)	−0.08**
=1 if production is second activity (%)	0.36 (0.48)	0.34 (0.47)	0.39 (0.48)	−0.05
=1 if parboiler is rice producer (%)	0.73 (0.44)	0.58 (0.49)	0.89 (0.31)	−0.31***
=1 if parboiler is Muslim (%)	0.59 (0.49)	0.27 (0.44)	0.91 (0.29)	−0.64***
=1 if Dendi ethnic group	0.53 (0.49)	0.18 (0.38)	0.88 (0.32)	−0.70***
=1 if Idaasha ethnic group	0.14 (0.35)	0.25 (0.43)	0.04 (0.18)	0.21***
=1 if Mahi ethnic group	0.21 (0.41)	0.38 (0.48)	0.04 (0.19)	0.34***
=1 if living in north region (%)	0.49 (0.50)	0.17 (0.37)	0.81 (0.39)	−0.65***
Institutional characteristics				
Distance to extension agent (km)	7.94 (4.48)	7.28 (4.07)	8.59 (4.78)	−1.31***
Distance to market (km)	3.30 (3.25)	3.39 (2.87)	3.20 (3.60)	0.19
Distance to town (km)	7.86 (5.17)	7.35 (5.03)	8.37 (5.26)	−1.03***
=1 if trained in GEM (%)	0.61 (0.48)	0.26 (0.43)	0.96 (0.19)	−0.70***
=1 if trained in parboiling activities	0.92 (0.27)	0.85 (0.36)	0.99 (0.12)	−0.14***
=1 if knowledge of GEM	0.77 (0.42)	0.55 (0.49)	1.00 (0.04)	−0.45***
=1 if contact with extension (%)	0.78 (0.41)	0.68 (0.46)	0.89 (0.31)	−0.21***
=1 if member of farm association (%)	1.00 (0)	1.00 (0)	1.00 (0)	0
=1 if has access to market information	0.97 (0.17)	0.97 (0.16)	0.96 (0.18)	0.01
=1 if has access to new varieties of rice	0.99 (0.12)	0.98 (0.13)	0.99 (0.09)	−0.01
=1 if has access to credit (%)	0.08 (0.26)	0.09 (0.29)	0.06 (0.23)	0.03*

***Significant at 1%, **Significant at 5%, *Significant at 10%, () standard deviation.

The findings showed that the lack of credit is the major constraint among rice parboilers in Benin. This constraint is seconded by the low availability of funds for the purchase of rice paddy. Many other constraints, such as the unavailability of areas for drying, the lack of training on improved techniques of parboiling, and the low storage capacity for parboiled rice were also seen to hinder parboilers from performing their work properly. Some constraints of less importance, such as the lack of knowledge of the price of rice and the unavailability of labor for sorting, were also mentioned.

4.1.2. Advantages of rice parboiling

Among the various advantages mentioned of parboiling rice, Kendall's test revealed that improving the quality of rice is the first and most important advantage according to the women parboilers (Table 5). Obtaining better nutritional value, reducing the volume of broken rice and attenuating the effect of bad drying (cracking) are also some key advantages identified as related to the parboiling of rice (Table 5). However, advantages such as better and longer storage, more resistance against insect attacks and avoiding the absorption of environmental humidity are also present in parboiling rice advantages.

TABLE 4 General constraints of rice parboiling activities.

Constraints	Mean rank	Rank
Lack of credit	3.68	1
Low availability of funds for the purchase of paddy	4.03	2
Unavailability of areas for drying	5.81	3
Lack of training on improved techniques of parboiling	6.39	4
Low storage capacity for parboiled rice	6.93	5
Low storage capacity for parboiled rice	7.54	6
Low physical quality of processed rice	7.69	7
Difficulty in obtaining packaging materials for parboiled rice	7.70	8
Problem of selling in the market	7.84	9
Mixing of rice varieties	8.13	10
Presence of foreign materials in the parboiled rice	8.20	11
No knowledge of paddy rice prices	8.43	12
No availability of labor for sorting	8.63	13
The Kendall's ranking test		
N	822	
Df	12	
Kendall's W	0.24	
Chi-square	2359.55***	

***Significant at 1%.

TABLE 5 Advantages of rice parboiling.

Parboiling advantages	Mean rank	Rank
Improve the quality of rice	3.03	1
Produce better nutritional value	3.21	2
Reduce the rate of brokenness of rice in milling	3.34	3
Attenuate the effect of bad drying (cracking)	3.92	4
Achieve better and lengthy storage	4.53	5
More resistance to insects' attack	4.94	6
Avoid the absorption of humidity of the environment	5.02	7
The Kendall's ranking test		
N	822	
Df	6	
Kendall's W	0.247	
Chi-square	1219.46***	

***Significant at 1%.

4.2. Determinant of adoption of the GEM parboiling system

We analyzed the drivers of the adoption of the GEM parboiling system, and the results are presented in Table 6. The model is globally significant at the 1% level, and 56% of the variation in the dependent variables is explained by the variation in the explanatory variables. The results showed that eight variables significantly drove the adoption of the GEM parboiling system. Knowledge and information indicators such as contact with extension agents, receiving training on the GEM parboiling system and having access to market information are positively associated with adopting the GEM parboiling system. This suggests that the likelihood of adopting the GEM parboiling system is higher for households that had access to information and knowledge than for those that did not. Furthermore, the distance to the extension agent is positively associated with the probability of adopting the GEM parboiling system.

The positive effect of contact with extension could be explained by the fact that most of the extension agents work in collaboration with AfricaRice for the training and dissemination of the improved GEM parboiling system. Thus, all women parboilers using the GEM system were in contact with extension agents who gave them training.

TABLE 6 Determinant of adoption of the GEM parboiling system.

Variables	Coefficients	Standard error
=1 if Dendi ethnic group	0.92***	0.26
=1 if parboiling is main activity (%)	−0.09	0.17
=1 if production is second activity (%)	0.00	0.17
=1 if belong to parboilers association	0.09	0.46
=1 if have contact with extension (%)	0.57***	0.16
=1 if trained in GEM (%)	1.76***	0.19
=1 if access to market information	0.66**	0.31
=1 if access to new varieties of paddy	0.73	0.45
Age of rice parboiler (year)	−0.01	0.01
Household size (Number)	0.01	0.02
=1 if female (%)	0.07	0.67
=1 if married (%)	−0.52**	0.25
=1 if parboiler has a formal education (%)	−0.05	0.13
=1 if parboiler is rice producer (%)	0.44**	0.17
Distance to extension agent (km)	0.04***	0.02
Distance to town (km)	0.02	0.01
Distance to market (km)	−0.08***	0.02
=1 if living in north region (%)	0.27	0.25
_ Constant	−3.55***	1.01
Number of observations	822	
Log of likelihood	−253.11	
Wald Chi-square	633.31***	
McFadden Pseudo R^2	0.56	

***Significant at 1%, **Significant at 5%.

The positive correlation between "participation in the GEM training" and adoption of the GEM system showed that in addition to making them aware of the technology, it enabled women to improve their skills in its use and increase the probability of adoption. The results also revealed that the coefficient of the variable representing "being married" and "distance to market" have a significant and negative influence on the use of the GEM system.

4.3. Impact of the GEM system on income, food security, and poverty reduction

This subsection presents the results from the endogenous switching regression model on the five main outcomes (income, output rate *per capita* food consumption expenditure, food consumption score, and poverty headcount ratio). Table A2 presents the estimated coefficients of the selection model on adopting the improved GEM system or nonadopters for different outcomes. The estimated coefficients of the selection terms are significantly different from zero, suggesting that both observed and unobserved factors influence the decision to adopt modern technology and welfare outcomes given the adoption decision. The result of the selection equation reveals that many variables are positively and significantly related to the adoption of the GEM system.

Table 7 shows the results of the impact of the adoption of the GEM parboiling system on the output rate. The expected quantity of milled rice per 100 kg of a bag of paddy under actual and counterfactual conditions is presented. We found evidence that the expected quantity of milled rice produced per bag of 100 kg of paddy by parboilers who adopted GEM technology is approximately 66.51 kg of milled rice.

In the counterfactual case (a), parboilers who actually adopted would have produced approximately 14.38 kg of milled rice per 100 kg (approximately 21.46%) less than if they did not adopt the GEM system for rice parboiling. Similarly, in the counterfactual case (b) that parboilers who did not adopt, they would have produced approximately 15.41 kg of milled rice (approximately 23.24%) more if they had adopted the GEM system. These results implied that the adoption of the GEM system significantly increases the rice output rate.

The impact of the adoption of the GEM parboiling system on income was also assessed (Table 8). The expected income per 100 kg of bag of paddy under actual and counterfactual conditions are presented. The results showed that the expected income per bag of 100 kg of paddy rice by parboilers who adopted the GEM system was approximately US$ 40.80.

In the counterfactual case (a), parboilers who actually adopted would have gained approximately US$ 7.25 per 100 kg of paddy (that is, approximately 17.77%) less if they did not adopt the GEM system

TABLE 7 Impact of the GEM parboiling system on output rate using the ESR method.

Treatment effect	Treatment type		Treatment effect	Change (%)
	Without adoption	With adoption		
Output rate of 100 kg of paddy (kg)				
Parboiler who adopted GEM system	(a) 52.24	(c) 66.51	ATT = 14.38***	21.46
	(0.08)	(0.02)	(0.07)	
Parboiler who did not adopt GEM system	(d) 50.91	(b) 66.32	ATUT = 15.41***	23.24
	(0.09)	(0.01)	(0.08)	

***Significant at 1%; () standard error.

TABLE 8 Impact of the GEM parboiling system on income using the ESR method.

Treatment effect	Treatment type		Treatment effect	Change (%)
	Without adoption	With adoption		
Income for 100 kg of paddy (US$)				
Parboiler who adopted GEM system	(a) 33.55	(c) 40.80	ATT = 7.25***	17.77
	(0. 08)	(0.13)	(0.10)	
Parboiler who did not adopt GEM system	(d) 30.93	(b) 35.73	ATUT = 4.81***	13.46
	(0.11)	(0.18)	(0.12)	

***Significant at 1%; () standard error.

TABLE 9 Impact of the GEM parboiling system on the food consumption score using the ESR method.

Treatment effect	Treatment type		Treatment effect	Change (%)
	Without adoption	With adoption		
Food consumption score (unit)				
Parboiler who adopted GEM system	(a) 70.62	(c) 84.03	ATT = 13.41***	15.96
	(0.17)	(0.18)	(0.28)	
Parboiler who did not adopt GEM system	(d) 67.26	(b) 86.28	ATUT = 19.02***	22.04
	(0.21)	(0.19)	(0.35)	

***Significant at 1%; () standard error.

for rice parboiling. Finally, in the counterfactual case (b) that parboilers did not adopt, they would have gained approximately US$ 4.81 (approximately 13.46%) more if they had adopted the GEM system. These results imply that adoption of the GEM system significantly increases women's parboiler income.

To assess the impact of the adoption of the GEM system on food security, we used two complementary indicators. We used the food expenditure and food consumption score (FCS). Table 9 presents the results of the impact of the adoption of the GEM parboiling system on the food consumption score.

We find evidence that in the counterfactual case (a), parboilers who actually adopted would have improved FCS in their household by approximately 13 points (approximately 15.96%) less if they did not adopt the GEM system for rice parboiling. Similarly, parboilers who did not adopt the GEM would have gained approximately 19 points (approximately 22.04%) more. These results imply that adoption of the GEM system significantly increases the food consumption score of women parboilers.

The results also showed that adoption of the GEM system reduced the food consumption expenditure of parboilers who adopted it by approximately US$ 72.63 (7.42%) (Table 10). Additionally, in the counterfactual case (b) of the parboilers who did not adopt, they would have increased their food consumption expenditure by approximately US$ 40.53 (approximately 4.99%) if they had adopted the GEM system.

Finally, the impact of the adoption of the GEM system on the poverty headcount ratio was assessed. We found evidence that in the counterfactual case (a), parboilers who actually adopted would have reduced the poverty headcount ratio in their household by approximately 5% more if they did not adopt the GEM system for rice parboiling (Table 11). In the counterfactual case (b) of parboilers who did not adopt, they would have been reduced by approximately 23% if they had adopted the GEM system. This is mainly because the adoption of the GEM system reduces the probability of poverty by nearly 5% for the average adopter, and the average untreated parboilers would have experienced a decrease in the poverty rate of approximately 23% by adopting the GEM system (Table 11). These results imply that the adoption of the GEM system significantly reduced the poverty headcount ratio in women's household parboilers.

TABLE 10 Impact of the GEM parboiling system on food consumption expenditures using the ESR method.

Treatment effect	Treatment type		Treatment effect	Change (%)
	Without adoption	With adoption		
Food consumption expenditure (US$/Year)				
Parboiler who adopted GEM system	(a) 1033.48	(c) 960.85	ATT = −72.63***	−7.56
	(9.66)	(4.88)	(7.42)	
Parboiler who did not adopt GEM system	(d) 770.98	(b) 811.51	ATUT = 40.53***	4.99
	(9.90)	(4.83)	(7.62)	

***Significant at 1%; () standard error.

TABLE 11 Impact of the GEM parboiling system on the poverty headcount ratio using the ESR method.

Treatment effect	Treatment type		Treatment effect	Change (%)
	Without adoption	With adoption		
Poverty headcount ratio (%)				
Parboiler who adopted GEM system	(a) 29	(c) 23	ATT = −5***	−26.09
	(11)	(13)	(1)	
Parboiler who did not adopt GEM system	(d) 39	(b) 15	ATUT = −23***	−61.54
	(10)	(14)	(1)	

***Significant at 1%; () standard error.

5. Discussion

To improve the physicochemical and nutritional value of the paddy rice produced in sub-Sahara Africa, AfricaRice has introduced the GEM system in many countries in the region. The objective of this study was to assess the drivers of adoption and impacts of the improved GEM parboiling system on the income, output rate, food security and poverty headcount ratio of women rice parboilers in Benin. The results showed that knowledge and information indicators such as contact with extension agents, being trained in the GEM parboiling system and having access to market information were positively associated with the probability of adopting the GEM parboiling system. Training in the GEM parboiling system and contact with extension agents have been found to positively impact the use of improved parboiling technology in Benin. This result is in line with the determinants of video technology adoption (Dandedjrohoun et al., 2012). Contact with agricultural extension services is supposed to facilitate better awareness, access to agricultural technologies and adoption (Jaleta et al., 2018). Membership in associations such as cooperatives enhances adoption by reducing information, credit, labor, and insurance market imperfections (Wossen et al., 2015). These results are in line with those of Zossou et al. (2009) who highlighted the importance of video screening in stimulating the adoption of improved technology in triggering local innovation. The results are also in line with the research from Zossou et al. (2022), who discussed the impact of information on technology adoption.

On average, the income of a random person selected among adopters of the GEM system increased by US$ 7.25 and the output rate increased by 14.38 kg per 100 kg of paddy rice after parboiling and dehulling. Adoption of the GEM system improves the food consumption score by 13.41 units in the population of adopters. Adoption of the GEM system increased the food consumption diversity in the household and decreased the food consumption expenditure in the population of adopters. This can be explained by the fact that the GEM system mainly aims to improve the physicochemical and nutritional quality, and all training and recent publications on the GEM system highlighted the nutrition aspect in rural areas (Ndindeng et al., 2015, 2022; Etoa et al., 2016; Zossou et al., 2022).

A lower poverty rate of 26% was found among households using the GEM system. The results were supported by women's perceptions that the output rate, quality of milled rice, better nutritional value and reduction of grain breakages during dehulling were major advantages of parboiling rice with the GEM system. These findings are in line with other previous research on parboiling activities. As reported by Ahiakpor et al. (2017), good appearance, good packaging and freedom from contaminants were the key traits that influenced consumers' choice of local rice in the Upper East Region. Ensuring better quality is necessary to obtain higher prices. As noted by Fofana et al. (2011), the use of traditional equipment and methods in parboiling results in high (90%) heat-damaged grains compared with the use of improved methods (17%). However, meeting the cost of improved processing vessels remains a challenge for most women parboilers. Training local fabricators in GEM systems of small, medium and large sizes should be promoted.

6. Conclusion and policy implications

This study assessed the impact of the improved GEM parboiling system on the livelihoods of women rice parboilers and the factors affecting the adoption of the GEM system and estimated its impact on income, output rate and food security in Benin. The improved GEM parboiling system has greater capacity than the traditional system. However, the high cost of the equipment limited its individual acquisition by women parboilers. In addition, different factors are positively and negatively correlated with the adoption of the GEM parboiling system, including “receiving training on GEM,” “having contact with extension agents,” “distance to extension agents,” and “having access to market information.” The GEM parboiling system adopters were found to have a lower rate of poverty (24%). This result suggests that the GEM parboiling system should be promoted among parboilers, as households with adopters of the GEM system suffer lower levels of poverty. In general, the findings indicate that the support and promotion of women parboilers training in GEM and having contact with extension agents is a means to increase technology uptake and access and subsequently improve their livelihoods. However, policy actions such as the training of local fabricators and credit options are required for the out-scale and sustainability of industrialization in Africa. Promotion of an innovation platform (IP) is a strategy to put all rice value chain actors together to work and have a common vision and defend their interest. Emerging opportunities in the rice sector that women and youth could take advantage of for better livelihoods and welfare could include sales to institutions, packaging, and government input subsidy programs.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

AA conceptualized the survey, design the data collection tools, contributed to the data analysis, and write the manuscript. RA contributed to the design of the data collection tools, data analysis, and contributed to write the manuscript. SA contributed to the survey design and review the manuscript. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

Supplementary material

The Supplementary material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fsufs.2023.1066418/full#supplementary-material

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Implementation of sustainable farming practices by cocoa farmers in Ecuador and Uganda: the influence of value chain factors

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A key strategy of chocolate manufacturers is the promotion of sustainable farming practices amongst their supplying cocoa producers. A growing body of micro-economic literature has analysed factors influencing the adoption of such practices, yet broadly disregarded value chain factors. Information on how factors *within* single value chains increase the adoption of sustainable farming practices can help direct chocolate companies' investments and increase return of investments in sustainability. The objective of this study was to understand: (a) how important value chain factors are, relative to farmer and farm factors, for cocoa farmers' implementation of sustainable farming practices and (b) through which mechanisms value chain factors influence sustainable farming practices implementation. By integrating the practice adoption with sustainable supply chain management literature, we contribute to closing an important research gap. We collected data from 394 cocoa farmers in Ecuador and Uganda and analysed the determinants of implementation sustainable farming practices, testing quantitatively whether value chain factors with variation *within* single value chains are significantly associated with practice implementation. These factors included information factors (farmers' access to training; advisory service through the value chain) and structural factors (value chain organisation and persistence; farmers' dependency on this value chain). We selected 11 sustainable farming practices or indicators across three sustainability dimensions, i.e., environmental, social, and economic. We found that value chain factors are comparable to farmer and farm factors in explaining the implementation of sustainable farming practices across dimensions. Both capacity building and stable relationships were significantly related with the implementation of certain sustainable farming practices. Yet these results were weaker than expected, indicating that their potential was not fully exploited within our case study value chains. Through their value chain sustainability initiatives, chocolate companies should disseminate knowledge, address inhibitors to sustainable farming practices implementation beyond knowledge, and align sustainability goals with all value chain actors.

KEYWORDS

cocoa, value chain, sustainability, practice adoption, sustainable supply chain management, capacity building, Ecuador, Uganda

1. Introduction

Global demand for sustainable chocolate is rising and with it, the pressure on chocolate companies to source sustainably produced cocoa. This has motivated several sustainability initiatives in the cocoa sector. Companies are increasingly sourcing certified cocoa or implementing their own in-house sustainability schemes (Thorlakson, 2018; Fountain and Huetz-Adams, 2020; Perez et al., 2020). A key strategy of both certification and corporate schemes is the promotion of sustainable farming practices or indicators (SFPI) amongst their upstream producers. We define SFPI to cover production practices that contribute to the performance in all three dimensions of sustainability (i.e., environmental, social, and economic).

A growing body of micro-economic literature has looked into factors that influence the adoption of such practices, which is summarised in several recent review studies (e.g., Meijer et al., 2015; Mozzato et al., 2018; Foguesatto et al., 2020; Takahashi et al., 2020). These conclude that the SFPI adoption literature has largely focussed on basic and extrinsic characteristics of the farmer and the farm, such as structure and resource endowments. Additionally, value chain factors, such as relationships between actors, are largely disregarded in existing frameworks (Mozzato et al., 2018). In contrast, the literature on value chain sustainability indicates that desirable (environmental) outcomes can be influenced by value chain partners (Hansson et al., 2019); through information sharing and economic dependencies (Grimm et al., 2014); and through strong and persistent relationships between actors – referred to as "stickiness" (Reis et al., 2020). There is thus a research gap in evaluating the influence of value chain related factors on farmers' adoption of SFPI (Mozzato et al., 2018; Candemir et al., 2021) and on how value chain partners can best increase knowledge and adoption of SFPI amongst small-scale farmers (Liverpool-Tasie et al., 2020). Furthermore, research on adoption of SFPI in cocoa has looked into environmental practices (e.g., Aneani et al., 2012; Djokoto et al., 2016; Ali et al., 2018), with less attention paid to the social and economic dimensions of sustainability (e.g., Nkamleu and Kielland, 2006; Amfo and Ali, 2020). These questions are important in the cocoa sector as the role of voluntary sustainability standards in transforming the food system towards more sustainability is ever more questioned (Meemken et al., 2021) and as influential downstream value chain actors are increasingly involved and invest in value chain sustainability. Particularly, knowing how factors *within* single value chains might increase the adoption of sustainable cocoa production practices can help direct investments and improve the cost-effectiveness of investments in sustainable value chains.

The objective of this study was to better understand the relationship between value chain factors and SFPI implementation, specifically aiming to identify *if* and *how* value chains influence farming practice adoption. In this study, we define value chain factors as those that describe information flow towards farmers as well as the organisation between and dependency of farmers and other value chain actors and thus contribute to the adoption literature. We posed two main research questions: (1) Relative to farmer- and farm-level factors, how important are value chain factors for cocoa farmers' implementation of sustainable farming practices?; and (2) Through which mechanisms do value chain factors influence SFPI implementation? Using our existing data set from two samples of cocoa farmers in Ecuador and Uganda, we analyse the determinants of implementation of 11 practices across three sustainability dimensions, testing quantitatively whether value chain factors *within* single value chains are significantly associated with practice implementation. We do this whilst controlling for farmer and farm factors known to influence practice implementation. By testing the role of value chain factors beyond the environmental dimension of sustainability in two very different cases, we aim to gain an indication of their broader significance and thus global value. This manuscript first provides an overview of relevant literature and the theoretical framework developed for this study, followed by a description of the case studies and selected analytical approaches. We then present the results and discuss them in light of our research questions and existing literature before providing concluding remarks.

2. Conceptual framework

Our conceptual framework combines selected SFPI, i.e., outcome variables, with covariates that might explain their implementation on farms. It is informed by underlying theory and literature on the adoption of SFPI amongst farmers. The conceptual framework for this study is based on the technology adoption and the sustainable value chain literature that links downstream actors with upstream sustainability outcomes. We chose the term practice "implementation" over "adoption," as many SFPI in cocoa production are traditional production practices and partly a legacy of past management instead of new practices that farmers actively decided to adopt on their farms.

2.1. Sustainable farming practices

Based on our existing identical data set from two producer groups, we identified practices from the environmental, social, and economic sustainability dimensions considered important for sustainable cocoa production (Table 1). We are aware that we do not cover all aspects of sustainability, like gender equality, phytosanitary measures, or living incomes. This was largely due to data limitations, as this study was conceptualised after primary data collection, and maintaining comparability across farms. For example, indicators such as gender equality could only be compared on a sub-sample of farms where both male and female employees were present, and thus was excluded from the analysis. Similarly, we did not identify the practice of "appropriate work for children" as an issue in the Ecuadorian case study, as children on sampled farms were hardly engaged in hazardous work. We recognise potential trade-offs between selected SFPI, such as potential negative effects of pesticide-free production on cocoa yields.

2.2. Theoretical considerations

Our conceptual framework is informed by the expected utility theory (Schoemaker, 1982) and the theory of planned behaviour (Ajzen, 1991). The expected utility theory adopts an economic rationale in which decision-making is based on greatest expected utility. It is considered relevant in the context of economically-constrained farmers who need to manage risk to secure their livelihoods (Meijer et al., 2015). Farmers' participation in sustainability initiatives and the compliance with respective codes of conduct might be a way to access better prices and thus maximise utility. Yet

TABLE 1 Overview of selected practices and indicators for sustainable cocoa production.

Analysed practice		Rationale for inclusion	Operationalisation
Environment	Pesticide-free production (1/0)	A wide variety of pesticides are used by farmers for pest and disease management in cocoa. Highly disputed Glyphosate and Paraquat are common herbicides, and Neonicotinoids and Pyrethroid common insecticides. Abstaining from using pesticides reduces the health risk for farmers and consumers, and reduces the environmental impact of cocoa production (Fountain and Huetz-Adams, 2020)	Takes 1 if farmers produced their cocoa without using any synthetic pesticides.
	Agroforestry (1/0)	Agroforestry systems can reduce the environmental impact of cocoa production through carbon sequestration, biodiversity conservation, soil fertility and moisture conservation, amongst others. Additionally, agroforestry systems have the potential to reduce deforestation associated with cocoa production (Kuyah et al., 2019; Fountain and Huetz-Adams, 2020)	Cocoa plots were observed during farm visits. Takes 1 if at least part of the cocoa was produced in an agroforestry system, defined here as the integration of cocoa with other shade trees in a minimum of three strata and with 5 non-cocoa tree species per hectare.
	Shade tree per hectare >12 (1/0)	Shade tree density can have beneficial environmental and agronomic properties. (UTZ, 2017; Blaser et al., 2018)	Farmers were asked about the number of permanent shade trees on their cocoa plots, which was then divided by the size of cocoa plots. Takes 1 if the threshold of 12 shade trees per hectare was met, adopted from UTZ certification requirements.
	Shade tree planting (1/0)	Planting shade trees on cocoa plantations can help reclaim forest environmental functions (Fountain and Huetz-Adams, 2020)	Farmers were asked if they had planted or nursed self-growing shade trees in their cocoa plots in the past year. Takes 1 if this was the case.
	Organic fertiliser use (1/0)	Nutrient limitation in cocoa fields is a major limiting factor to improve productivity (van Vliet and Giller, 2017).	Takes 1 if farmers applied organic fertilisers.
Social	Use of personal protective equipment (1/0)	Cocoa farmers are exposed to numerous health and occupational risks, for example during farm activities like spraying of chemicals, cutting, weeding and harvesting. The use of personal protective equipment like gloves, safety glasses, and boots can avoid physical harm during these activities (de Bon et al., 2014; Boadi-Kusi et al., 2016)	Farmers were asked about what they wear during potentially harmful tasks. Takes 1 if the equipment worn was sufficient to provide protection.
	Appropriate work by children (1/0)	More than one million children work on cocoa plantations globally, mainly in West Africa (Fountain and Huetz-Adams, 2020). Whilst the mere involvement of children in farm work is not *per se* regarded as negative, it becomes an issue when their physical and/or mental development is harmed (ILO, n.d.). Hazardous tasks performed by children in cocoa production include carrying heavy loads or working with pesticides and sharp tools. Our indicator does not consider the length of working hours and time of day when the work is carried out. Additionally, country-specific minimum employee ages were not applied. Instead, we used 16 years as a generic cut-off for this indicator. Thus, it does not fully assess hazardous child labour as qualified by ILO.	Farmers were asked about the tasks performed by their children or hired workers <16 years of age. Takes 1 if these tasks did not pose any risk for children.
	Workers' daily wage (USD/day)	Hiring seasonal workers is common in cocoa production. Workers in rural areas in cocoa producing countries often face precarious working conditions, without contracts, and low wages (Meemken et al., 2019; Fountain and Huetz-Adams, 2020)	In case farms hire workers, farmers were asked about the lowest daily wage they paid. In Uganda, wages were mostly paid per task instead of per day. Here, the wage for a typical task was divided by the average number of days required for their completion.
Economic	Farm revenues (USD/year)	Numerous reports suggest that a large share of cocoa farming household live below the poverty line (Waarts et al., 2019; van Vliet et al., 2021) and the call for living incomes for cocoa farmers become louder (Fountain and Huetz-Adams, 2020; Fountain and Huetz-Adams, 2022). Whilst not able to measure incomes, farm revenues represent an indication of the economic benefits that farmers generate on farm.	Farmers were asked about the quantities of each product sold and the respective average price per unit sold.

(Continued)

TABLE 1 (Continued)

Analysed practice		Rationale for inclusion	Operationalisation
	Cocoa yields (tons/ha)	Low yields are often reported from cocoa production systems, with economic implications for farming households. Increasing cocoa yields is regarded as one step towards achieving living incomes for cocoa farming households (van Vliet et al., 2021).	Farmers were asked about the sizes of all cocoa plots as well as the cocoa harvest from each plot in the reference year. Farm yields represent the plot size-weighted average yield per farm. Fresh cocoa bean weight was converted to dry bean weight using the conversion factor 0.38.
	Secure farm succession (1/0)	Youth migration to the cities creates labour shortage, leaving behind an ageing population of cocoa farmers that is unable to afford hiring labour and keep up proper crop management (Dormon et al., 2004; Mithöfer et al., 2017; Abdulai et al., 2020). A defined successor of cocoa farms can ensure continuous investment in productive farms.	Farmers above the age of 55 years were asked about a successor. Takes 1 if a clear candidate has been identified.

decision-making is not always purely rational and often influenced through social-psychological pathways, which is what the theory of planned behaviour aims to understand. According to this theory, attitude, subjective norms, and perceived behavioural control shape an individual's behavioural intentions, which again is considered the closest determinant of behaviour. Participation in sustainability initiatives and the training sessions offered to farmers within these initiatives, and gaining first-hand experiences with SFPI might influence farmers' attitude towards them and ultimately shape farmers' intention to implement them. With these theories as a basis, our conceptual framework builds on the agricultural technology adoption literature and the sustainable supply chain literature that links downstream actors with upstream sustainability outcomes.

2.2.1. Agricultural technology adoption literature

A growing body of micro-economic literature has looked into factors that influence farmers' adoption of sustainable farming practices, mainly regarding agro-environmental practices. The large number of recent review studies is evidence of this trend, each proposing different frameworks based on reviewed studies (Meijer et al., 2015; Liu et al., 2018; Mozzato et al., 2018; Arslan et al., 2020; de Oca Munguia and Llewellyn, 2020; Foguesatto et al., 2020; Piñeiro et al., 2020). Most frameworks distinguish between factors within and factors beyond the farm.

Factors within the farm most commonly include farmers' socio-demographic factors like age and education level. Past studies have shown a mixed influence of farmer factors on practice adoption. In line with the theory of planned behaviour, farmers with higher education levels or higher awareness about environmental threats, for example, might be more informed about sustainability issues and thus more likely to implement SFPI across all sustainability dimensions (Nkamleu and Kielland, 2006; Boadi-Kusi et al., 2016; Amfo and Ali, 2020). Contrarily, female farm managers might be less likely to implement or adopt a new technology as they might face structural inequalities, such as lower access to education or production factors (Djokoto et al., 2016).

Additionally, farm factors are included in most SFPI adoption frameworks, including farm structure and management. Past studies found that farms' economic situation positively influences the adoption of environmental, social, and economic practices as a result of greater access to resources and necessary inputs. For example, more resource endowed farmers have shown to be more likely to hire labour and thus involve less children in hazardous tasks (Berlan, 2013; Busquet et al., 2021). Furthermore, a lack of labour can reduce the implementation of labour-intensive environmental practices (Andres et al., 2016). Secure land tenure can furthermore have a positive effect on SFPI adoption and investments in green practices (Useche and Blare, 2013; Yang et al., 2022). Finally, the cocoa variety has been shown to strongly influence environmental practices, as hybrid varieties, such as the Ecuadorian CCN-51, require higher inputs and tolerate less shade (Rueda et al., 2018).

Factors beyond the farm-level include the biophysical, spatial, socio-economic, and policy environment in which farms operate. Proximity to urban centres and markets might increase farmers' access to information and inputs and thus increase SFP implementation (Foguesatto et al., 2020). Furthermore, social norms and networks can influence SFPI adoption (Liu et al., 2018). Finally, the practice characteristics themselves are important influencing factors. For example, cost-intensive practices might obstruct their adoption (de Oca Munguia and Llewellyn, 2020) especially on low-income smallholder farms. Labour-constrained households might be more willing to adopt labour-saving technologies (Arslan et al., 2020).

2.2.2. Sustainable supply chain literature

Commercial partners within value chains can influence practice adoption amongst farmers (Hansson et al., 2019), for example through incentives or regulatory measures (Piñeiro et al., 2020). Examples include performance-based price premiums and sustainability certification. Cocoa value chains are characterised by a highly diffuse producer base of many small-scale producers and a concentrated downstream actor level, with increasing power (Thorlakson, 2018).

Past research in the value chain literature has focused on compliance of upstream partners with sustainability requirements of downstream companies. Grimm et al. (2014) identified critical factors for achieving supplier compliance, grouping them into factors within and beyond downstream companies. The former includes top management support, which positively influences companies' commitment and available resources for value chain sustainability mechanisms. The latter includes information sharing and commitment between value chain partners. A large body of literature has shown the importance of information sharing through training and extension for practice adoption in cocoa production systems (e.g., Andres et al., 2016; Denkyirah et al., 2016; Okoffo et al., 2016), often provided by downstream value chain actors.

A recent study linked persistent relationships in value chains with sustainability outcomes under the concept of "stickiness" and showed

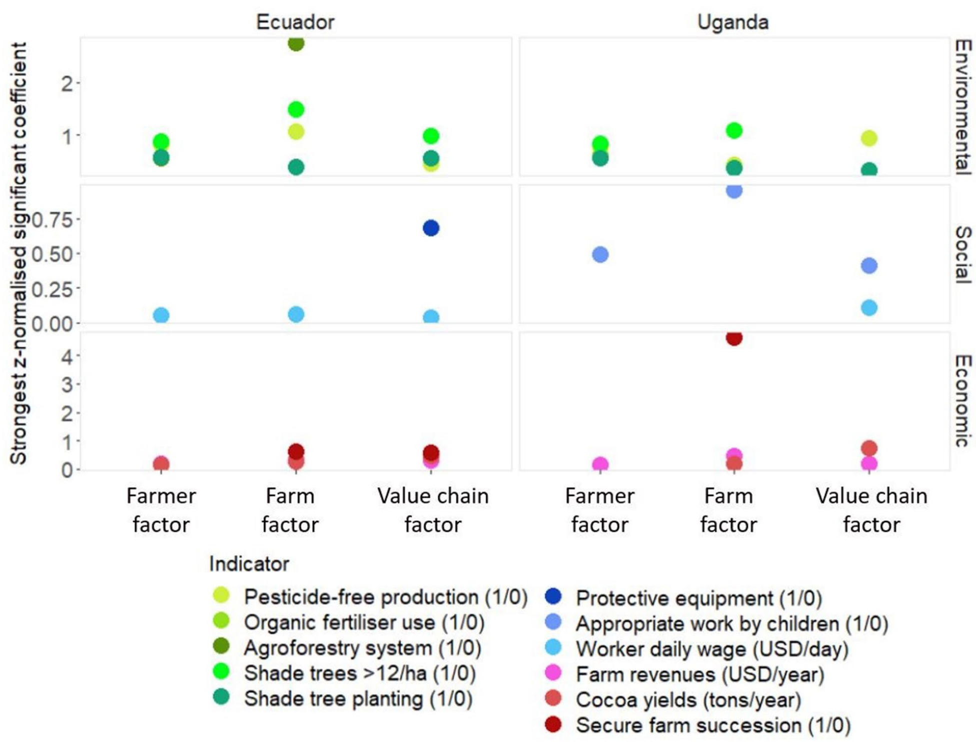

FIGURE 1
Comparison of strongest z-normalised significant coefficient among farm, farmer, and value chain factors for each sustainable farming practice and country.

that more persistent soy value chains in Brazil are more effective in creating change in sustainability performance amongst upstream producers (Reis et al., 2020). Furthermore, upstream actors' economic dependence might increase compliance with downstream companies' sustainability codes of conduct (Grimm et al., 2014). As such, farmers with a higher economic dependency on cocoa for their livelihoods, a greater dependency on one buyer with certain sustainability codes of conduct, and generally fewer cocoa buyers might implement more SFPI.

2.3. Selected covariates

As the literature review displays, a great range of factors have been shown to influence practice implementation or adoption. The selection of groups of factors and specific factors to include in our analysis was restricted by our existing data set. To assess the importance of value chain factors for the adoption and implementation of sustainable cocoa production practices, we controlled for other factors known to influence their implementation. We organised factors influencing SFPI into two groups of internal and external factors (Figure 1). An overview of factors and rationale for their inclusion can be found in the supplementary materials.

2.3.1. Internal farmer factors

The set of farmer factors controlled for included farmers' age, gender, and formal education years. We additionally incorporated farmers' expressed commitment to sustainability (dummy) and knowledge about climate change (dummy). Given the literature shown above, we hypothesise that farmer factors, specifically farmers' knowledge and conviction, are highly important for the decision to implement SFPI in our case studies (Hypothesis 1).

2.3.2. Internal farm factors

Incorporated farm factors comprised multiple indicators for farms' economic endowment, including farm and cocoa plot size (hectares), land ownership (dummy), and livestock units owned (number). Labour availability on farm was covered by the number of family workers. In the Ecuadorian case study, we added the hybrid cocoa variety CCN-51 as a predictor (dummy). Given the mixed picture presented in past studies, we assume that farm factors are less important for SFPI implementation (Hypothesis 2).

2.3.3. Value chain factors

We considered both information sharing and organisation as important value chain variables. Within information factors, we included the number of training days farmers participated in (days/year) and farmers' perceived access to extension services (dummy). These two variables account for farmers' access to private training and advisory service organised by downstream value chain actors. Additionally, we considered factors that describe the value chain organisation and persistence, adapting the stickiness definition by Reis et al. (2020) to our cross-sectional data. We included farmers' economic dependency on cocoa (share of gross farm revenue from cocoa) and their main customer (share of gross farm revenue from main buyer). Furthermore, we included the number of cocoa buyers per farmer and the years of relationship with the main cocoa buyer. Based on first evidence reviewed above, we hypothesise that downstream value chain actors have several mechanisms available with which they can generate a change in SFPI implementation at farm level, thus value chain factors are important for SFPI implementation (Hypothesis 3). We specifically tested two mechanisms: (a) Information factors, covering farmers' access to capacity building through the value chain, which we presume to be a suitable mechanism for downstream value chain actors to increase SFPI implementation amongst their suppliers (Hypothesis 4); and (b) Structural factors, including value chain organisation and persistence as well as farmers' dependency on this value chain. Our final hypothesis follows the assumption that the mechanism of establishing long-term and stable relationships along value chains create trust and thus increase SFPI implementation (Hypothesis 5).

3. Materials and methods

3.1. Case study description

We addressed our research questions and related hypotheses with a comparative case study approach. In order to get comprehensive insights into the cocoa sector, we selected two diverse value chains. They connect cocoa farmers in Ecuador and Uganda to downstream Swiss chocolate companies.

3.1.1. Ecuador

Ecuador is the world's fifth largest producer of cocoa, with almost 330,000 tonnes produced in 2020 (FAO, 2022a), and is the largest producer of fine flavour cocoa, known in Ecuador as Cacao Nacional (Anecacao, n.d.). The majority of the 527,347 ha of land used for cocoa cultivation in Ecuador in 2020 (FAO, 2022b) was located in the coastal area (INEC, 2020), which is also the location of the sampled farmers in this case study.

The Swiss chocolate company at the downstream end of this cocoa value chain is a large multinational chocolate manufacturer, which sources cocoa from Ecuador through an in-house sustainability programme. This programme was introduced in the country in 2014 and has gradually increased in size, including almost 6,000 independent farmers in 2019. Farmers are grouped around intermediaries in the closest town, which also form part of the sustainability programme. Finally, a large multinational trading company buys cocoa from intermediaries and exports it to Europe. The exporter is also in charge of implementing the sustainability programme, mainly focussing on cocoa traceability, farmer training, in-kind premium distribution, and community development. Farmers receive "normal" market prices for their cocoa, dependent on its quality and humidity content. They additionally receive in-kind premiums, which included mineral fertilisers, fungicides, or tools. Programme farmers are not contractually obliged to sell their cocoa to programme intermediaries, yet no longer receive premiums if they frequently sell elsewhere. Farmers in the programme undergo several training modules with a strong focus on good agricultural practices and environmental protection. Each intermediary group, ranging in size from 100 up to 600 farmers, generally has one farmer trainer. Most trainings sessions are held at the intermediary shop in town and farmers are motivated to participate in these sessions as they are combined with the distribution of premiums. Farmer trainers rarely pay additional visits on individual farms given the high number of farmers.

3.1.2. Uganda

In comparison to Ecuador, Uganda had a much smaller cocoa production in 2020 of 35,000 tonnes, harvested from 70,809 ha (FAO, 2022b). National production quantities and export values, however, have been increasing steadily (FAO, 2022b). Major cocoa producing areas in Uganda are Bundibugyo in the Western and Mukono in the Central Region, the latter being the location of the cocoa producers in our second case study value chain.

In this case study, around 500 independent farmers in Mukono District have been converting to certified organic production for three years at the time of data collection. In 2017, a national export company searching to increase its supplier base in Mukono District recruited farmers based on a door-to-door method asking for their willingness to comply with organic regulation in exchange for higher cocoa prices. This export company started the certification process with the promise to buy farmers' cocoa and vanilla with a price premium once certified. For organic certification, the export company established an internal control system, which includes yearly controls on farms to ensure their compliance with the organic standard. In order to provide knowledge about certification and organic production practices, a training programme with four modules was initiated. Farmers were invited to participate in trainings. The export company hired two farmer trainers to cater to the group of farmers in Mukono District, who are in charge of the trainings and compliance control. The downstream Swiss chocolate brand is relatively young and small, and caters to a niche market of sustainable chocolate consumers. The owners personally know the lead farmer and the conditions in which farmers in Mukono District live and operate.

3.2. Farmer sampling and data collection

Farmer sampling followed a randomised approach in both case studies, targeting sample sizes of around 200 farmers, which was feasible within the project framework. We selected a random sample of farmers within each case study. In Ecuador, we selected eight intermediary groups in four provinces of north-western Ecuador and then randomly selected a subsample of 25 farmers per group, totalling 190 farmers. In Uganda, we made a random selection of 204 farmers across the entire farmer group of around 450 farmers.

Trained enumerators and the lead author visited the selected farms between July and September 2019 in Ecuador and February and March 2020 in Uganda to undertake face-to-face interviews with farm managers [more details in Tennhardt et al. (2022)]. At each farm, we applied the SMART-Farm Tool (Schader et al., 2016, 2019) as described in Tennhardt et al. (2022), to derive a large indicator pool on farm management and sustainability indicators. In addition, we collected contextual data on the farmer, farm, and the cocoa supply chain. We collected all information for the reference years of 2018 in Ecuador and 2019 in Uganda. Data collection was performed in accordance with all relevant institutional and national ethical guidelines. It followed free and informed consent by farmers, which was obtained orally from respondents and documented with a signature in a participation list.

3.3. Data analysis

We ran multivariate mixed regression models for each case study, using individual practices as dependent variables and the set of predictors including value chain factors as explanatory variables. Dependent variables were binary and continuous (Table 1) and thus required different types of regression models. In each model, we checked for multicollinearity using variance inflation factors and deleted predictors with values >3. We z-normalised all predictors to facilitate comparison between predictors with differing scales (Bruce et al., 2020).

We approached the estimation of value chain factors' importance for SFPI implementation being aware that certain predictors might be endogenous to dependent variables and reverse causality might exist, potentially leading to biased estimates. Thus, we refrained from interpreting any result as impacts and any mention of an effect refers to a change in probability, not to a causal effect. Additionally, we do not use data to predict adoption but rather explain current implementation.

We controlled for a potential "village bias," i.e., a potential correlation amongst close-by farms due to information exchange amongst neighbours, locally-specific training offers, or local conditions such as topography or road infrastructure. Due to the uneven distribution of farms per village, especially in the Ugandan case, not all mixed models converged when adding the village as a random effect. Therefore, we developed a standard procedure, which was applied to all models: First, we fit each model with only village as a random effect and without other covariates. If the simple model converged, we added all covariates as fixed effects and kept village as a random effect. If the full model converged, we kept it and interpreted the results. If the full model did not converge after the second step, we introduced the village as a fixed effect instead of as a random effect and checked if the village had a significant effect. If the village showed a significant effect, we kept it and interpreted the results. If the village did not show a significant effect, we removed it as a fixed effect and interpreted the estimates of the model without village. If the simple model did not converge after the first step, we introduced the village as a fixed effect instead of as a random effect and checked if the village had a significant effect. If the village was significant, we kept it and interpreted the results. If the village was not significant, we removed it as a fixed effect and interpreted the estimates of the model without village. This approach was considered the best middle ground between accounting for a potential village bias where possible and simplifying the models where necessary.

All statistical analyses were performed in R (vers. 4.1.0, R Project for Statistical Computing, RRID:SCR_001905), via RStudio (vers. 2022.02.01 + 461, RStudio, Q19 RRID:SCR_000432). The analysis was implemented in RStudio's RMarkdown script format, which integrates analysis, reporting, and export functions for highly reproducible research reports (Baumer and Udwin, 2015). Data and code are available here.[1]

1 https://figshare.com/s/d25ecd539209287d7b1e

3.3.1. Binary dependent variables

Most of the SFPI in our database had binary response options, i.e., were applied (=1) or not applied on a farm (=0). This dichotomous division is typical in studies that aim at modelling the adoption of agricultural practices (Foguesatto et al., 2020) and allows for a clear differentiation between farms that implemented and farms that did not implement a certain practice. We modelled the effects of predictors on binary SFPI using generalised linear mixed models (GLMM) in case the model converged with the village variable introduced as a random effect, and generalised linear model (GLM) otherwise, after confirming the insignificance of the fixed variable "village" (see supporting information). We used glmmTMB() function of the R package glmmTMB for GLMM including village as random effect, glm() function of the R package stats for GLM, and Anova() from the R package car to test for significance of "village" as fixed effect.

3.3.2. Continuous dependent variables

We employed linear mixed regression models (LMM) for continuous dependent variables and log-transformed dependent variables due to skewed data. In those cases where the mixed models did not converged with the village variable as a random effect, we applied Ordinary Least Square (OLS) regression. We used the lmer() function of the R package lme4 for LMM including "village" as random effect and the lm() function of the R package stats for OLS models.

3.3.3. Simultaneous models

Some SFPI selected in this study are related and not entirely independent of other selected SFPI. As an example, the dependent variable cocoa yields might influence the dependent variable farm revenues. Not accounting for these interdependencies generates a potential bias (Grovermann et al., 2023). In order to test for this bias and verify the robustness of the results of the isolated models, we ran simultaneous models. We estimated multivariate probit models for binary dependent variables with interdependency (i.e., agroforestry systems, shade tree planting, and shade tree density). Furthermore, we estimated seemingly unrelated models for continuous dependent variables with interdependency (i.e., gross farm revenues and cocoa yields). The results of these models are presented in the supplementary materials.

4. Results

4.1. Descriptive statistics results

Table 2 shows the descriptive results of the dependent variables analysed in the environmental, social, and economic dimensions of sustainability as well as the independent farmer, farm, and value chain variables. Most dependent and independent variables show a distribution suitable for further analyses with regression models, with some exceptions: organic fertiliser use in Ecuador and engagement of children in hazardous work was low and further regression analyses were not carried out. Similarly, the use of protective equipment was low and growing cocoa in agroforestry systems was high in Uganda. All farms in the Ecuadorian sample owned some sort of livestock and we excluded this predictor from the regression models for this case study.

4.2. Relative importance of value chain factors (hypotheses 1, 2, and 3)

The results of the different regression models testing the influence of value chain variables on SFPI implementation in the environmental dimension for the Ecuadorian and Ugandan case studies are presented in Tables 3, 4. The results for the social and economic dimensions for the Ecuadorian and Ugandan case studies are shown in Tables 5, 6. Furthermore, the strongest coefficient (β) of significant predictors per factor group and SFPI are shown in Figure 2.

4.2.1. Practices within the environmental dimension

Within the Ecuadorian case study, factors from all three groups of predictors showed significant relationships with environmental SFPI (Table 3). We found strong predictors amongst the group of farm factors (Figure 2). Farm size showed a significant and positive relationship with growing cocoa in agroforests (GLMM, $\beta = 2.53$, $n = 175$, $p < 0.05$), yet larger cocoa plots were significantly and negatively associated with shade tree density (GLMM, $\beta = -1.48$, $n = 173$, $p < 0.01$). Growing the hybrid cocoa variety CCN-51 was significantly and negatively related to growing cocoa in agroforestry systems (GLMM, $\beta = -1.12$, $n = 175$, $p < 0.01$) and pesticide-free production (GLMM, $\beta = -1.07$, $n = 175$, $p < 0.001$). Holding all other variables constant, the odds for farms growing hybrid cocoa to practice pesticide-free cocoa production were 66% lower than for farmers not growing hybrid cocoa. The farmer factor farmers' commitment to sustainability also showed a significant and positive association with pesticide-free production (GLMM, $\beta = 0.81$, $n = 175$, $p < 0.01$) and shade tree density (GLMM, $\beta = 0.89$, $n = 175$, $p < 0.01$). The strongest value chain factor with a coefficient of -0.99 was farmers' dependency on cocoa revenues, which showed a significant negative relationship with agroforestry systems (GLMM, $n = 173$, $p < 0.05$).

Also in the Ugandan case study, all three groups of predictors showed significant relationships with environmental SFPI (Table 4). The number of training days represented the strongest value chain factor, which was significantly and positively associated with pesticide-free production (GLM, $\beta = 0.94$, $n = 182$, $p < 0.01$). This indicates that with an increase of 4.3 training days and holding all other variables constant, the odds of producing pesticide-free cocoa increased by 156%. The farmer factor commitment to sustainability showed a significant and positive relationship with pesticide-free production (GLM, $\beta = 0.77$, $n = 182$, $p < 0.001$) and shade tree planting (GLM, $\beta = 0.57$, $n = 182$, $p < 0.01$), yet a negative relationship with shade tree density (GLM, $\beta = -0.84$, $n = 182$, $p < 0.05$).

4.2.2. Practices within the social dimension

Our covariates showed rather weak predicting power for the implementation of social SFPI amongst sampled Ecuadorian farmers (Table 5). Farmers reported that they had received some personal protective equipment, such as rubber boots, through the sustainability programme. Training participation was significantly and positively associated with the use of protective equipment (GLMM, $\beta = 0.63$, $n = 146$, $p < 0.05$). The average daily wage for a farm worker in this case study was 14 USD. As reported by farmers, wages partly depend on the tasks (e.g., manual weeding receives a lower wage than using an electric grass cutter due to the higher risk involved), the gender of the worker with women often receiving lower daily wages, and farmers' ability to pay. Farmers' commitment to sustainability showed a significant and positive relationship with wages (LMM, $\beta = 0.05$, $n = 127$, $p < 0.05$).

TABLE 2 Mean values (standard deviation) and percentages of dependent variables and predicting factors for sustainable practice implementation in cocoa.

		Ecuador ($n = 190$)	Uganda ($n = 204$)
Environmental	Pesticide-free production = Yes	34.2%	60.8%
	Agroforestry system = Yes	57.4%	98.0%
	Shade trees >12/ha = Yes	70.2%	81.4%
	Shade tree planting = Yes	18.9%	49.0%
	Organic fertiliser use = Yes	14.2%	65.7%
Social	Use protective equipment = Yes	32.1%	7.9%
	Worker daily wage (USD/day)	14.08 (3.08)	1.80 (1.07)
	Appropriate work by children = Yes	96.8%	78.9%
Economic	Gross farm revenues (USD/year)	5,754 (6517)	1,641 (2276)
	Cocoa yields (ton/ha)	0.30 (0.34)	0.36 (0.45)
	Secure farm succession = Yes	56.8%	53.9%
Farmer factors	Age (years)	51.56 (13.70)	52.81 (12.84)
	Female = Yes	23.7%	31.9%
	Formal education (years)	7.74 (4.03)	5.58 (4.59)
	Verbal commitment to sustainability = Yes	36.3%	77.0%
	Climate change knowledge = Yes	48.4%	57.4%
Farm factors	Farm size (hectares)	12.56 (16.31)	2.82 (2.97)
	Cocoa area (hectares)	5.00 (3.79)	1.30 (1.30)
	Secure land tenure = Yes	90.5%	87.3%
	Livestock units (number)	6.96 (14.99)	1.13 (1.73)
	Family workers (number)	2.16 (1.13)	3.81 (2.39)
	Hybrid cocoa variety = Yes	55.8%	NA
Value chain factors	Access to extension service = Yes	50.5%	70.1%
	Training days (days/year)	2.32 (2.90)	2.76 (4.27)
	Dependency cocoa revenue (% farm revenue)	0.58 (0.34)	0.42 (0.31)
	Dependency main customer (% farm revenue)	0.67 (0.27)	0.59 (0.23)
	Cocoa buyers (number)	1.17 (0.47)	1.34 (0.84)
	Relationship with cocoa buyers (years)	8.08 (7.31)	1.1 (4.03)

NA, not applicable.

TABLE 3 Multivariate mixed regression models for sustainable farming practices and indicators in cocoa production systems in Ecuador – results for practices in the environmental dimension.

Ecuador		Pesticide-free production (1/0)	Agroforestry system (1/0)	Shade trees > 12/ha (1/0)	Shade tree planting (1/0)
Environmental practices		*GLMM[a]*	*GLMM[a]*	*GLMM[a]*	*GLMM[a]*
z-normalised predictors		β (SE)	β (SE)	β (SE)	β (SE)
Farmer factors	Farmer age (years)	−0.42 (0.27)	0.42 (0.27)	0.38 (0.25)	−0.32 (0.26)
	Female = Yes	−0.28 (0.25)	0.11 (0.26)	−0.25 (0.23)	−0.3 (0.25)
	Formal education (years)	**−0.53. (0.32)**	0.43 (0.28)	**0.43. (0.25)**	−0.22 (0.28)
	Verbal commitment to sustainability = Yes	**0.81** (0.26)**	0.04 (0.28)	**0.89** (0.29)**	0.27 (0.23)
	Climate change knowledge = Yes	0.02 (0.25)	**−0.56* (0.27)**	−0.34 (0.24)	**0.59* (0.25)**
Farm factors	Farm size (hectares)	0.06 (0.45)	**2.53* (1.13)**	2.75 (1.7)	−0.01 (0.43)
	Cocoa area (hectares)	−0.34 (0.33)	−0.06 (0.38)	**−1.48** (0.55)**	0.28 (0.29)
	Land ownership = Yes	−0.24 (0.25)	0.22 (0.28)	0.05 (0.25)	0.14 (0.24)
	Livestock units (#)	−0.2 (0.41)	**−2.74* (1.11)**	0.87 (1.35)	0.54 (0.41)
	Family workers (#)	0.13 (0.24)	−0.17 (0.27)	−0.1 (0.24)	**0.39. (0.23)**
	Hybrid cocoa variety = Yes	**−1.07*** (0.3)**	**−1.12** (0.37)**	−0.4 (0.31)	−0.34 (0.28)
Value chain factors	Access to extension = Yes	**−0.47 (0.27)**	−0.07 (0.31)	**−0.62* (0.3)**	**0.57* (0.29)**
	Training days (#/year)	0.13 (0.28)	0.71 (0.48)	0.58 (0.41)	−0.38 (0.28)
	Dependency cocoa revenue (% farm revenue)	−0.48 (0.38)	**−0.99* (0.42)**	**−0.98* (0.41)**	0.27 (0.35)
	Dependency main customer (% farm revenue)	−0.09 (0.34)	0.39 (0.41)	0.33 (0.4)	−0.3 (0.32)
	Cocoa buyers (#)	−0.41 (0.31)	**0.58* (0.27)**	0.1 (0.25)	0.03 (0.23)
	Relationship cocoa buyers (years)	**−0.57* (0.27)**	0.04 (0.31)	**0.51. (0.31)**	−0.09 (0.25)
Constant		**−1.26** (0.41)**	0.64 (0.64)	**2.58*** (0.67)**	**−1.75*** (0.29)**
Observations		175	175	173	175
Marginal N&S R^2 – GLMM		0.492	0.477	0.789	0.273
Conditional N&M R^2 – GLMM		0.578	0.708	0.827	0.300

Marginal Nakagawa & Schielzeth's R2 GLMM, proportion of variance by fixed factors alone; Conditional Nakagawa & Schielzeth's R2 GLMM, proportion of variance by fixed and random factors. β, estimated coefficient; SE, standard error. [a]Generalised linear mixed models (with village as random effect). ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, $p < 0.1$.

Workers on farms in the Ugandan sample received on average 1.8 USD per day. Ugandan farmers mostly pay workers per task, requiring an estimation of the associated workload. Training days were significantly and positively associated with paid wages (LMM, $\beta = 0.11$, $n = 114$, $p < 0.1$). Furthermore, most farms in this case study included children up to 16 years of age in farming activities. For the vast majority of children, farm work did not impair their school assistance or performance as they engaged during school holidays or the weekend. However, on 21% of sampled farms, children were involved in hazardous work like using sharp tools or spraying pesticides. The number of family workers as farm factor showed the strongest relationship with this outcome variable (GLM, $\beta = -0.95$, $n = 181$, $p < 0.001$). Farmers' dependency on their main customer, contrarily, showed significant and positive relationships with appropriate work by children (GLM, $\beta = 0.41$, $n = 181$, $p < 0.1$).

4.2.3. Practices within the economic dimension

All factor groups showed significant relationships with economic SFPI within our Ecuadorian sample (Table 5; Figure 2). Female farmers had significantly lower gross farm revenues and cocoa yields (LMM, $\beta = -0.17$ and -0.16, $n = 173$, $p < 0.05$). Whilst the number of livestock units and cocoa plot size showed a significant and positive relationship with gross farm revenues (LMM, $\beta = 0.29$ and 0.35, $n = 175$, $p < 0.1$), cocoa plot size showed a significant and negative relationship with yields (LMM, $\beta = -0.3$, $n = 175$, $p < 0.05$). Finally, farmers' dependency on cocoa revenues showed a significant and negative relationship with gross farm revenues (LMM, $\beta = -0.29$, $n = 175$, $p < 0.01$), yet a significant and positive relationship with cocoa yields (LMM, $\beta = 0.47$, $n = 173$, $p < 0.001$). This indicates that, holding all other variables constant, with a 34% increase in the share of farm revenues from cocoa, cocoa yields increase by 60%.

TABLE 4 Multivariate mixed regression models for sustainable farming practices and indicators in cocoa production systems in Uganda – results for practices in the environmental dimension.

Uganda		Pesticide-free production (1/0)	Organic fertiliser (1/0)	Shade trees > 12/ha (1/0)	Shade tree planting (1/0)
Environmental practices		*GLM*[b]	*GLMM*[a]	*GLM*[b]	*GLM*[b]
z-normalised predictors		β (SE)	β (SE)	β (SE)	β (SE)
Farmer factors	Farmer age (years)	0.15 (0.19)	−0.25 (0.19)	0.24 (0.27)	**−0.38* (0.19)**
	Female = Yes	0.21 (0.2)	**0.61** (0.21)**	−0.26 (0.27)	**−0.32. (0.19)**
	Formal education (years)	−0.1 (0.2)	**0.62** (0.21)**	0.02 (0.26)	0.21 (0.19)
	Verbal commitment to sustainability = Yes	**0.77*** (0.19)**	0.24 (0.19)	**−0.84* (0.35)**	**0.57** (0.2)**
	Climate change knowledge = Yes	−0.06 (0.19)	−0.11 (0.2)	**0.68* (0.27)**	−0.11 (0.19)
Farm factors	Farm size (hectares)	**−0.43* (0.2)**	0.26 (0.42)	**−0.9* (0.37)**	−0.15 (0.31)
	Cocoa area (hectares)		−0.13 (0.35)		0.23 (0.31)
	Land ownership = Yes	0.02 (0.17)	0.07 (0.18)	0.09 (0.25)	0.19 (0.17)
	Livestock units (#)	−0.19 (0.18)	0.22 (0.22)	**1.09* (0.46)**	0.08 (0.18)
	Family workers (#)	0.02 (0.19)	0.09 (0.18)	−0.27 (0.24)	**0.37** (0.18)**
Value chain factors	Access to extension = Yes	0.19 (0.19)	0.24 (0.19)	0.24 (0.24)	**0.32. (0.18)**
	Training days (#/year)	**0.94** (0.36)**	0.3 (0.22)	−0.02 (0.22)	−0.09 (0.17)
	Dependency cocoa revenue (% farm revenue)	**−0.51* (0.22)**	0.05 (0.22)	−0.16 (0.29)	−0.09 (0.21)
	Dependency main customer (% farm revenue)	0.27 (0.21)	−0.19 (0.2)	0.44 (0.27)	**−0.34. (0.19)**
	Cocoa buyers (#)	0.16 (0.2)	0.03 (0.2)	−0.11 (0.25)	−0.15 (0.19)
	Relationship cocoa buyers (years)	−0.09 (0.17)	−0.07 (0.18)	0.46 (0.4)	−0.08 (0.19)
Constant		**0.59** (0.19)**	**0.74** (0.25)**	**2.38*** (0.35)**	−0.24 (0.17)
Observations		181	181	181	181
Nagelkerke pseudo R^2		0.298		0.335	0.278
Marginal N&S R^2 – GLMM			0.217		
Conditional N&M R^2 – GLMM			0.270		

Marginal Nakagawa & Schielzeth's R2 GLMM, proportion of variance by fixed factors alone; Conditional Nakagawa & Schielzeth's R2 GLMM, proportion of variance by fixed and random factors; β, estimated coefficient; SE, standard error. [a]Generalised linear mixed models (with village as random effect), [b]Generalised linear model. ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, $p < 0.1$. Bold values where $p<0.05$.

The results of the Ugandan case study mirror several findings from the Ecuadorian data (Table 6). As such, the share of revenues generated by cocoa showed a significant and positive relationship with cocoa yields (LMM, $\beta = 0.74$, $n = 164$, $p < 0.001$), female farmers generated lower gross farm revenues (LMM, $\beta = -0.16$, $n = 164$, $p < 0.1$), and farm size and the number of livestock units were significantly and positively related to gross farm revenues (LMM, $\beta = 0.47$ and 0.15, $n = 164$, $p < 0.1$).

In summary, we found the largest number of significant relationships within our models estimating SFPI implementation in the environmental dimension, with lowest explanatory power of our models estimating SFPI implementation in the social dimension (Figure 2). The relative importance of value chain factors to explain SFPI implementation was similar to the importance of intrinsic farmer and farm factors within all sustainability dimensions.

4.3. Value chain mechanisms that influence SFPI implementation (hypotheses 4 and 5)

We tested the relationship of two value chain factor subgroups, i.e., mechanisms of value chain influence, and SFPI implementation at farm level. These were information and organisational factors.

4.3.1. Information factors

Within both samples, few information factors were significantly associated with the implementation of SFPI. Amongst Ecuadorian farmers, training days showed a significant and positive relationship with the use of protective equipment (GLMM, $\beta = 0.63$, $n = 173$, $p < 0.05$, Table 5) and access to advisory service was negatively associated with pesticide-free cocoa production (GLMM, $\beta = -0.47$, $n = 173$, $p < 0.1$, Table 3). Amongst Ugandan farmers, training days were significantly and positively associated with pesticide-free

TABLE 5 Multivariate mixed regression models for sustainable farming practices and indicators in cocoa production systems in Ecuador – results for practices in the social and economic dimensions.

Ecuador		Use of protective equipment (1/0)	Worker daily wage [ln(USD/day)]	Gross farm revenue [ln(USD/year)]	Cocoa yields [ln(ton/ha)]	Secure farm succession (1/0)
Social and Economic practices		*GLMM[a]*	*LMM[b]*	*LMM[b]*	*LMM[b]*	*GLMM[a]*
z-normalised predictors		β (SE)	β (SE)	β (SE)	β (SE)	β (SE)
Farmer factors	Farmer age (years)	0.25 (0.26)	0.01 (0.02)	−0.06 (0.07)	−0.06 (0.08)	0.05 (0.29)
	Female = Yes	0.00 (0.24)	−0.01 (0.02)	**−0.17* (0.07)**	**−0.16* (0.07)**	−0.19 (0.25)
	Formal education (years)	0.21 (0.26)	0.02 (0.02)	0.08 (0.07)	0.02 (0.08)	−0.27 (0.28)
	Verbal commitment to sustainability = Yes	0.36 (0.24)	**0.05** (0.02)**	0.1 (0.07)	0.09 (0.08)	0.41 (0.3)
	Climate change knowledge = Yes	0.09 (0.24)	**−0.04* (0.02)**	0.02 (0.07)	0.07 (0.07)	0.19 (0.27)
Farm factors	Farm size (hectares)	0.72 (0.57)	−0.06 (0.04)	0.15 (0.15)	0.02 (0.17)	1.25 (1.52)
	Cocoa area (hectares)	−0.27 (0.3)	−0.01 (0.02)	**0.35*** (0.09)**	**−0.27** (0.1)**	−0.27 (0.47)
	Land ownership = Yes	−0.12 (0.28)	−0.01 (0.02)	−0.06 (0.07)	−0.06 (0.07)	0.15 (0.28)
	Livestock units (#)	−0.55 (0.56)	0.03 (0.03)	**0.29* (0.14)**	0.19 (0.16)	−0.54 (0.94)
	Family workers (#)	−0.25 (0.26)	**−0.05* (0.02)**	−0.07 (0.07)	−0.09 (0.07)	**0.62. (0.32)**
	Hybrid cocoa variety = Yes	0.4 (0.32)	**0.06** (0.02)**	0.02 (0.09)	−0.03 (0.1)	0.08 (0.31)
Value chain factors	Access to extension = Yes	0.3 (0.3)	−0.01 (0.02)	−0.05 (0.08)	−0.07 (0.09)	−0.15 (0.29)
	Training days (#/year)	**0.63* (0.32)**	0.02 (0.02)	0.09 (0.08)	0.14 (0.09)	0.05 (0.35)
	Dependency cocoa revenue (% farm revenue)	**−0.68. (0.36)**	−0.04 (0.03)	**−0.29* (0.1)**	**0.47*** (0.11)**	−0.16 (0.37)
	Dependency main customer (% farm revenue)	0.19 (0.34)	**0.04. (0.02)**	−0.03 (0.09)	−0.04 (0.1)	**0.59. (0.35)**
	Cocoa buyers (#)	−0.11 (0.28)	0.02 (0.02)	0.01 (0.07)	0.04 (0.07)	0.13 (0.26)
	Relationship cocoa buyers (years)	0.2 (0.24)	0 (0.02)	0.02 (0.07)	−0.1 (0.08)	0.27 (0.33)
Constant		**−1.15** (0.38)**	**2.61*** (0.03)**	**8.1*** (0.21)**	**−1.77*** (0.21)**	**1.71*** (0.4)**
Observations		146	127	175	173	123
Marginal N&S R^2 – GLMM		0.258	0.194	0.387	0.224	0.369
Conditional N&M R^2 – GLMM		0.383	0.283	0.589	0.447	0.396

Marginal Nakagawa & Schielzeth's R2 GLMM, proportion of variance by fixed factors alone; Conditional Nakagawa & Schielzeth's R2 GLMM, proportion of variance by fixed and random factors. β, estimated coefficient; SE, standard error. [a]Generalised linear mixed models (with village as random effect), [b]Linear mixed model (with village as random effect). ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, $p < 0.1$. Bold values where $p<0.05$.

production (GLM, $\beta = 0.94$, $n = 182$, $p < 0.01$, Table 4). In Ecuador (GLMM, $\beta = 0.57$, $n = 173$, $p < 0.05$, Table 3) and Uganda (GLM, $\beta = 0.32$, $n = 181$, $p < 0.1$, Table 4), farmers with access to extension were more likely to plant shade trees in their cocoa plots. In conclusion, we found limited evidence for hypothesis 4 that information sharing and capacity building along value chains increases the implementation of a large number of SFPI at farm level.

4.3.2. Organisation factors

Organisation factors showed some important significant relationships with SFPI implementation. The most significant predictor was farmers' dependency on cocoa revenues, which showed several significant relationships. In the Ecuadorian case, farms with greater dependency on cocoa were less likely to have a shade tree density of above 12 trees per hectare (GLMM, $\beta = -0.98$, $n = 173$, $p < 0.05$, Table 3), grow cocoa in agroforestry (GLMM, $\beta = -0.99$, $n = 173$, $p < 0.05$), use personal protective equipment (GLMM, $\beta = -0.68$, $n = 146$, $p < 0.1$, Table 5), and had lower gross farm revenues (LMM, $\beta = -0.29$, $n = 175$, $p < 0.01$), yet higher cocoa yields (LMM, $\beta = 0.47$, $n = 173$, $p < 0.001$). This trend was partly mirrored in the Ugandan case, where dependency on cocoa revenues was significantly and positively associated with cocoa yields (OLS, $\beta = 0.74$, $n = 168$, $p < 0.001$, Table 6) and showed a significant negative relationship with pesticide-free production (GLM, $\beta = -0.51$, $n = 182$, $p < 0.05$), whilst dependency on the main customer was significantly and negatively associated with shade tree planting (GLM, $\beta = -0.34$, $n = 181$, $p < 0.1$, Table 4). Long-term relationships with cocoa buyers were significantly and negatively associated with pesticide-free production in Ecuador (GLMM, $\beta = -0.57$, $n = 175$, $p < 0.05$, Table 3) but showed a significant positive relationship with cocoa yields in the Ugandan case (OLS,

TABLE 6 Multivariate mixed regression models for sustainable farming practices and indicators in cocoa production systems in Uganda – results for practices in the social and economic dimensions.

Uganda		Appropriate work by children (1/0)	Worker daily wage [ln(USD/day)]	Gross farm revenue [ln(USD/year)]	Cocoa yields [ln(ton/ha)]	Secure farm succession (1/0)
Social and Economic practices		GLM[a]	LMM[b]	LMM[b]	OLS[c]	GLM[d]
z-normalised predictors		β (SE)	β (SE)	β (SE)	β (SE)	β (SE)
Farmer factors	Farmer age (years)	0.05 (0.24)	0.08 (0.06)	−0.11 (0.08)	−0.11 (0.08)	0.29 (0.51)
	Female = Yes	−0.07 (0.24)	−0.04 (0.07)	**−0.16. (0.08)**	−0.1 (0.08)	0.12 (0.52)
	Formal education (years)	−0.08 (0.23)	0.07 (0.07)	0.04 (0.08)	0.03 (0.08)	−0.37 (0.46)
	Verbal commitment to sustainability = Yes	−0.14 (0.24)	0.02 (0.06)	0.00 (0.08)	0.11 (0.08)	0.1 (0.41)
	Climate change knowledge = Yes	**−0.49* (0.25)**	−0.03 (0.06)	0.07 (0.08)	−0.11 (0.08)	0.36 (0.48)
Farm factors	Farm size (hectares)	0.76 (0.58)	−0.01 (0.1)	**0.47** (0.14)**		0.84 (0.8)
	Cocoa area (hectares)	0.04 (0.45)	0.02 (0.09)	0.05 (0.13)	**−0.17* (0.07)**	
	Land ownership = Yes	0.25 (0.19)	−0.03 (0.06)	0.04 (0.07)	−0.05 (0.07)	0.17 (0.42)
	Livestock units (#)	−0.19 (0.21)	0.01 (0.05)	**0.15. (0.08)**	**0.17* (0.08)**	
	Family workers (#)	**−0.95*** (0.23)**	−0.02 (0.06)	0.09 (0.08)	−0.08 (0.08)	**4.62* (1.94)**
Value chain factors	Access to extension = Yes	−0.14 (0.23)	−0.03 (0.06)	0.05 (0.08)	0.08 (0.08)	−0.67 (0.6)
	Training days (#/year)	0.4 (0.27)	**0.11 (0.06)**	0.07 (0.08)	−0.07 (0.07)	0.05 (0.66)
	Dependency cocoa revenue (% farm revenue)	0.01 (0.25)	0.01 (0.07)	0.1 (0.09)	**0.74*** (0.09)**	−0.44 (0.54)
	Dependency main customer (% farm revenue)	**0.41. (0.22)**	0 (0.06)	**−0.19* (0.08)**	**−0.18* (0.08)**	0.14 (0.46)
	Cocoa buyers (#)	−0.19 (0.22)	0 (0.06)	0.1 (0.08)	0.1 (0.09)	1.03 (0.71)
	Relationship cocoa buyers (years)	0.13 (0.26)	−0.04 (0.05)	0.04 (0.08)	**0.16* (0.08)**	−0.51 (0.32)
Constant		**1.71*** (0.25)**	**0.44*** (0.06)**	**6.79*** (0.09)**	**−1.63*** (0.07)**	**6.2** (2.02)**
Observations		181	114	181	168	109
Adapted R^2					0.334	
Nagelkerke pseudo R^2		0.285				0.592
Marginal N&S R^2 – GLMM			0.071	0.341		
Conditional N&M R^2 – GLMM			0.085	0.351		

Marginal Nakagawa & Schielzeth's R2 GLMM, proportion of variance by fixed factors alone; Conditional Nakagawa & Schielzeth's R2 GLMM, proportion of variance by fixed and random factors. β, estimated coefficient; SE, standard error. [a]Generalised linear model, [b]Linear mixed model (with village as random effect), [c]Ordinary least square model, [d]Generalised linear mixed model (with village as random effect). $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $p < 0.1$. Bold values where $p<0.05$.

$\beta = 0.16$, $n = 168$, $p < 0.05$, Table 6). These results indicate that value chain organisation and stability can influence SFPI implementation at farm level providing evidence for hypothesis 5.

5. Discussion

Our study tested the relative importance of external value chain factors compared to internal farmer and farm factors in explaining SFPI implementation on cocoa farms across the environmental, social, and economic dimensions of sustainability. It furthermore examined two specific mechanisms within value chains for their relationships with SFPI implementation, namely information provision through and organisation of the value chain. We observed strong differences across practices and sustainability dimensions in terms of which factors influenced SFPI implementation. Despite some differences between case studies, we also identified a few reoccurring important factors. This suggests that the factors influencing adoption of SFPI are partly context dependent and cannot be generalised across the board. As a result, the supporting evidence for the various hypotheses was more nuanced and contextual. All three groups of factors showed significant relationships with the implementation of SFPI across sustainability dimensions, yet

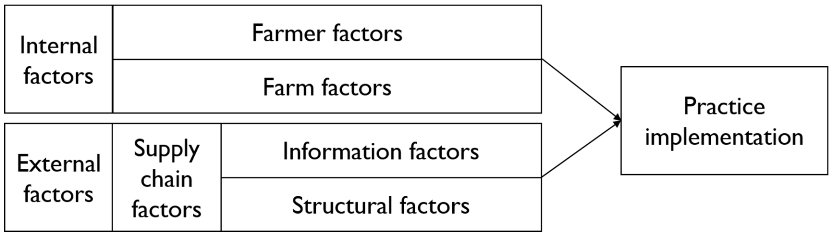

FIGURE 2
Conceptual framework of factors influencing sustainable practice implementation on cocoa farms.

were strongest for environmental SFPI. We discuss these results in detail in relation to our original hypotheses below.

5.1. Relative importance of value chain factors

5.1.1. Intrinsic farmer factors are important for SFPI implementation (Hypothesis 1)

From the farmer factor group, significantly associated predictors mainly cover farmers' intrinsic motivation and go beyond SFPI implementation in the environmental dimension. These results confirm the importance of intrinsic and attitudinal factors for SFPI implementation (Meijer et al., 2015; Bijani et al., 2017; Dessart et al., 2019; Bazrafkan et al., 2022).

5.1.2. Farm factors show mixed results for SFPI implementation (Hypothesis 2)

Our models included multiple factors that represent farmers' economic endowment, which have been shown to be positively associated with practices that require financial investments (Arslan et al., 2020). We observed some important relationships in our results, such as farm and cocoa plot size and the number of livestock units, which were positively related to gross farm revenue generation in both case studies. Remarkably, no significant relationship was identified between farm economics and the use of personal protective equipment, as previously found by Boadi-Kusi et al. (2016), Okoffo et al. (2016), and Owombo et al. (2014). This indicates that farmers' economic situation is not solely responsible for SFPI implementation. Our results for Uganda furthermore support the notion that the relationship between farms' economic endowment and hazardous child labour is not unidirectional and more complex (Berlan, 2013; Busquet et al., 2021). In our case, larger households with more members involved in farm work were more likely to involve children in hazardous tasks, which is contrary to past findings from Côte d'Ivoire (Nkamleu and Kielland, 2006). Finally, cocoa yields decreased with increasing cocoa plot sizes in both case studies, in line with past findings (Bymolt et al., 2018).

Current demographic changes are affecting cocoa farming systems, as farmers report ageing managers and labour shortage (Mithöfer et al., 2017). This especially affects SFPI that are considered labour intensive, such as good cocoa management practices (Armengot et al., 2019) or agroforestry systems (Armengot et al., 2016). Farms with more family workers in our samples were more likely to implement the laborious task of shade tree planting and have a secure farm succession. This is in line with studies from Atube et al. (2021), who found that larger household sizes were positively associated with the adoption of labour intensive farming practices in Uganda. More generally, however, and in light of recent demographic changes in cocoa growing communities, the relationship between labour availability and SFPI implementation should receive additional attention.

Finally, our results mirror prior research on the role of the hybrid cocoa variety CCN-51, which is becoming more common amongst Ecuadorian cocoa farmers due to its relative disease resistance and higher productivity (Boza et al., 2014). Farmers with the hybrid cocoa variety CCN-51 were more likely to apply synthetic pesticides and grow cocoa in full-sun systems compared to the fine flavour cocoa variety, in line with past findings (Bentley et al., 2004; Blare and Useche, 2013; Middendorp et al., 2018; Rueda et al., 2018). Contrasting these past findings, growing hybrid cocoa was not accompanied by economic co-benefits in our case study.

5.1.3. Value chain factors are comparatively important for SFPI implementation (Hypothesis 3)

Our results highlight the importance of all predictor groups for SFPI implementation in the environmental dimension, supporting past research on the importance of value chains for environmental decision-making at farm level (Hansson et al., 2019; Liverpool-Tasie et al., 2020). Our results also highlight a similar importance of value chain factors and intrinsic farm and farmer factors in the social and economic dimensions, which was not known before.

5.2. Value chain mechanisms that influence SFPI implementation

5.2.1. Information can be a relevant factor for SFPI implementation (Hypothesis 4)

In general, value chain factors regarding information flow showed few relationships with SFPI implementation, and these could be explained based on existing farmer training programmes. In the Ecuadorian case, the sustainability programme promoted the use of personal protective equipment and these were handed to farmers during trainings. Past studies also found clear relationships between access to extension service and the use of protective equipment amongst cocoa farmers in Ghana, Nigeria, and Cameroon (Owombo et al., 2014; Boadi-Kusi et al., 2016; Okoffo et al., 2016). In this value chain, the Swiss chocolate company's in-house sustainability programme is the only source of advisory service or training on cocoa production for most of the sampled farmers. Governmental advisory services were scarce and farmers' level of organisation for joint commercialisation was low, as is the case amongst Ecuadorian cocoa farmers in general (Huetz-Adams et al., 2016). This highlights the important role of corporate capacity building in delivering services to farmers that are underprovided by the state.

In the Ugandan case, farmers who had participated in more training days were more likely to produce pesticide-free cocoa despite our observations that all farmers had access to agro-shops and thus pesticides. This is in line with farmers' conversion to organic certification at the time of data collection as the restriction of synthetic pesticides was an important topic in the export company's trainings to prepare farmers for the upcoming audit. However, since training participation is voluntary, causality could be reversed due to positive selection bias, with farmers who used no or few pesticides more eager to take part in trainings. Voluntary training participation and the delay in payment of price premiums might also explain that almost 40% of sampled farmers were not complying with organic regulation. Low compliance rates have been reported from certified cocoa producers in Ghana, pointing to the need to further invest in capacity building and compliance verification (Ansah et al., 2020; Schader et al., 2021). Regardless, our results suggest that farmer training can be an important aspect for SFPI adoption, in line with past studies that identified positive effects of training or cooperative membership on practice implementation (e.g., Effendy et al., 2019; Piñeiro et al., 2020; Adebayo et al., 2021; Musafiri et al., 2022).

Our results did not show a relationship between training and advisory service and other SFPI, despite Ecuadorian farmers receiving training on topics such as cocoa management practices to increase productivity and growing cocoa in agroforestry systems for product diversification. This indicates implementation constraints beyond knowledge. For example, Useche and Blare (2013) found that Ecuadorian farmers who prioritised a fast economic return rather grew cocoa in monoculture systems.

5.2.2. The value chain organisation can be an important factor for SFPI implementation (Hypothesis 5)

The relationships between value chain organisation factors and SFPI implementation observed in our samples were weaker than expected and sometimes even negative. In the Ecuadorian case, long-term relationships with intermediaries reduced the likelihood of pesticide-free cocoa production. This could in part be due to the double agency role of intermediaries, as both buyers of cocoa and sellers of inputs. Reports from farmers suggest that long-standing relationships with local intermediaries facilitated the receipt of loans or inputs, which farmers repay with the next cocoa harvest. For pest or disease management, many Ecuadorian cocoa farmers seek advice from input providers (Blare and Useche, 2014), highlighting their importance for reducing synthetic pesticide use in cocoa. Reis et al. (2020) demonstrated that stable relationships between value chain partners can improve the sustainability performance by comparing *between* value chains. Our results indicate that long-term relationships *within* single value chains can also influence SFPI implementation, yet only when all actors involved share the same sustainability goals. In our two cases, downstream chocolate manufacturers aimed to reduce pesticide residues in cocoa and thus their use on farms, whilst input-supplying intermediaries distributed synthetic pesticides and provided loans for them.

Our results also highlighted significant relationships regarding farmers' economic dependency. In the Ecuadorian case, farms' dependency on cocoa revenues was negatively associated with gross farm revenues. At the time of data collection, cocoa prices in Ecuador were relatively low and some farmers had already or planned to switch to more attractive commodities, such as passion fruit. In Uganda, however, cocoa prices were higher than those for traditional commodities, such as coffee. A higher dependence on cocoa revenues and thus specialisation, however, increased farms' cocoa yields across cases, yet at the expense of shade tree density and planting. These results support the notion that income diversification strategies, especially when cocoa prices are low, are important for smallholder livelihoods and resilience (Aneani et al., 2011; Cerda et al., 2014), despite potentially reducing downstream companies' power to enforce rules for sustainable cocoa production (Grimm et al., 2014). Ecuadorian farmers in our sample who diversify their cocoa buyers too much are sanctioned by no longer receiving in-kind premiums, a threat commonly associated with sustainability initiatives (Grabs and Carodenuto, 2021). Thus, promoting diverse agroforestry systems and income diversification might require a balancing act from downstream companies to ensure living incomes and resilient systems for supplying farmers whilst not losing too much leverage to generate change in cocoa farming practices.

Farm workers' wages have recently received attention with potential implications for value chains. Farmers in our case studies paid their workers 70% of the national minimum wage (Ecuador) and 18% of the estimated living wage (Uganda) (Global Living Wage Coalition, 2021; Wage Indicator, 2022). Low wages are generally perceived as a result of commercial value chain practices with uneven value distribution and low prices paid by buyers (Lebaron, 2021), following which farmers are not able to pay adequate wages. Meemken et al. (2019) assessed the effect of Fairtrade certification on cocoa farm workers' annual wages in Côte d'Ivoire and concluded that given current payment modalities, smallholder farmers were not incentivised to pay higher wages without clear rules and their monitoring.

5.3. Limitations and future research directions

In this study, we show several significant relationships between value chain factors and SFPI, whilst controlling for numerous confounding factors. This illustrates the importance of value chain factors despite the lack of attention paid to them in the literature thus far. However, some caveats are required in the interpretation of results due to several limitations in our study design. First, the results are largely exploratory and causal inference between value chain factors and sustainability outcomes should be avoided due to potential endogeneity issues. Future studies on the adoption of SFPI should therefore consider an experimental approach that controls for endogeneity, potentially with instrumental variables. Second, our farmer sample might not represent a sample of "typical" Ecuadorian and Ugandan cocoa farmers but rather farmers from the "sustainable cocoa" segment and part of specific value chains with sustainability orientation. Thus, our results are generalisable only to a certain extent. Third, we were limited to the data set available and several potentially important groups of factors were thus not included in our analysis, such as the broader economic or climatic situation. The importance of attitudinal and social aspects for practice adoption is increasingly recognised (Meijer et al., 2015; Dessart et al., 2019; Arslan et al., 2020), which we were only partly able to cover. Our study furthermore did not cover the role of (financial) incentives, which can be a strong element in farmers' decision making (Piñeiro et al., 2020). Also the role of additional contextual factors like the broader economic situation or climatic conditions. In the future, different value chain characteristics including incentives could be combined with an in-depth analysis of farmers' social setting and motivation to implement or adopt certain practices to determine their importance.

6. Conclusion

Chocolate companies are increasingly investing in value chain sustainability initiatives, highly focusing on sustainable practice uptake amongst upstream producers. Yet little is known about if and how value chain factors influence practice implementation, especially within the social and economic dimension of sustainability. Our results from two cocoa value chains connecting cocoa producers in Ecuador and Uganda with Swiss chocolate brands revealed the most important conclusion: value chain factors can have a substantial influence on the implementation of SFPI amongst cocoa producers. Whilst observed relationships were weaker than hypothesised, our results indicate that value chain factors are just as important as farmer and farm factors for SFPI across sustainability dimension. Whilst this study was rather exploratory in nature, it provides evidence that future studies on farmers' adoption of sustainable practices should integrate value chain characteristics into their conceptual frameworks.

Our results highlight that chocolate brands have various levers within their own value chains to improve the sustainability performance of their supplying farmers and assure the long-term supply of sustainably produced cocoa. However, their potential was underexploited in both case studies. Capacity building is an important mechanism for downstream actors to increase SFPI implementation at farm level, especially when training and extension target specific practices. Training and extension service organised by downstream companies should therefore address specific practices beyond agro-environmental practices. In addition, resource transfer might provide farmers with the necessary resources to enact change. In our case studies, this is currently done through in-kind premium distribution and promised price premiums, yet could be extended to address inhibiting factors for practice implementation beyond knowledge. Our results furthermore suggest that stable and long-term relationships between value chain actors can influence SFPI implementation on farms, yet require a common definition of sustainability goals. Chocolate manufacturers should clearly define and communicate their sustainability goals along the entire value chain and align all actors in order to avoid contradictory agendas from single parties. In order to fully exploit the potential to generate change, chocolate companies need to continuously invest and establish strong collaborations along their entire value chain.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found at: https://figshare.com/s/d25ecd539209287d7b1e.

Ethics statement

The studies involving human participants were reviewed and approved by Ethics committee of the Department of Food Systems Sciences, Research Institute of Organic Agriculture (FiBL). Written informed consent for participation was not required for this study in accordance with the national legislation and the institutional requirements.

Author contributions

LT, EL, MC, and CS contributed to conception and design of the study. LT performed the investigation, statistical analysis, and wrote the first draft of the manuscript. All authors contributed to manuscript revision, read, and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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Determinants of farmers' willingness to pay for improved cultivars of *Macrotyloma geocarpum* (harms) Maréchal and Baudet in Benin and Togo

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Introduction: Quality seed is essential to satisfy food demand. This is also true for neglected crops especially those that are economically valuable such as Kersting's groundnut (*Macrotyloma geocarpum*), which holds the potential to improve farmers' livelihoods. In this study, we assessed the attributes that drove Kersting groundnut farmers' willingness to pay for improved seeds.

Methods: A total of 567 respondents were selected in the Northern Guinea and Southern Sudanian production zones in Benin and Togo using chain referral sampling, and they were then interviewed with a semi-structured questionnaire. Classification and regression trees, Ordinary Least Squared, and Tobit regression were combined to assess the relationship between the socio-demographic variables and farmers' Willingness to Pay (WTP) and Amount they are Willing to Pay (AWTP).

Results and discussion: Results suggested that more than 90% of respondents involved in the production of *Macrotyloma geocarpum* were willing to access its improved seeds, including those who had already abandoned the cultivation of this crop due to constraints such as the very low seed yield of current cultivars, the difficulty to access seeds, and the cultivation practices. The factors which affected the amount farmers are willing to pay included the following: the low yield of current cultivars used by farmers, the expected yield of the improved variety, which should be higher than 1 ton per ha ($1\,t.ha^{-1}$), the socio-linguistic group affiliation, and the adoption level of improved agricultural technologies. The average amount fixed by seed companies that farmers were willing to pay for 1 kg of the improved seed was USD 5.35 but they have freely proposed to pay the average amount of USD 4.63 to access 1 kg of improved seed. The white-seeded cultivar was the most appreciated by farmers and was the most cultivated in the Northern Guinean Zone whereas the cultivation of the colored-seeded (e.g., black-seeded) cultivars was mainly noted in the Southern Sudanian Zone. Furthermore, the respondents indicated seed yield improvement and disease management as their main research needs to help increase the production of the crop. The findings of this research will help refine *Macrotyloma geocarpum* improvement programs to release farmer-needed varieties.

KEYWORDS

orphan legumes, technology adoption, breeding traits, improved cultivars, *Macrotyloma geocarpum*

1. Introduction

The extent of food insecurity in Africa (and in Sub-Saharan Africa in particular), the growing population in the region, and a changing climate suggest that many efforts are required to end hunger. In this context, policies that aim to strengthen food security need to implement actions based on evidence related to factors that are likely to affect the availability and accessibility of quality food. Increasing food diversification through sustainable intensification of crop production programs can help fight hunger and reduce poverty. In Africa, climate change is one of the main threats to agricultural productivity due to erratic rainfall patterns, unpredicted floods and droughts, and unexpected temperature fluctuations, and these have severe consequences on food and nutrition security (Zougmoré et al., 2018). Through rising temperatures crop productivity in Africa will continue to decrease. Agriculture is facing the challenges of climate change, and as the backbone of food production, a more diverse crop production system is required to meet food demand in terms of both quantity and acceptable quality (Waha et al., 2018) for the increasing population. Agricultural diversification systems appear as a sound solution to climate change with the development of improved and resilient varieties and the cultivation or domestication of new crops (Sognigbé and Tchokponhoué, 2020).

Since agricultural production in Sub-Saharan Africa is mainly rainfed, the impact of unfavorable weather on yields is more pronounced, with severe consequence on the subsistence and incomes of smallholder farmers (Callo-Concha et al., 2013). Historically, only a few crops (e.g., wheat, maize, and rice) constitute the basis of food security worldwide and are well integrated into most agricultural policies. Unfortunately these major crops only represent 2.14% of the existing crop diversity (Padulosi et al., 2013). In West Africa, local communities refer predominantly to some orphan crops (neglected crops) for their food needs (Ebert, 2014) while most of these orphan plants have no established crop improvement programs to support the development of improved varieties.

One of the most used crop groups by local population are leguminous crops. They are an important commodity group owing to the multi-purpose nature of their member species. They can help regenerate soil through nitrogen fixation, and they constitute a good source of vegetal protein (Graham and Vance, 2003; Considine et al., 2017). They also exhibit a great ecological adaptability with resilient attributes for adaptation to climate change (Considine et al., 2017; Cullis and Kunert, 2017). Some of the leguminous crops are well cultivated and supported by crop improvement programs (e.g., cowpea and soybean), while a number of them are still in the orphan stage without much attention from research. *Macrotyloma geocarpum* (Harms) Maréchal & Baudet, known as Kersting's groundnut (also referred to as *doyi*, the local name used in Benin), is an economically valuable legume crop in Benin and West Africa that can be used in diversifying food and income generation (Achigan-Dako and Vodouhè, 2006). However, the potential of the species is being hindered by its continuously decreasing production. This could be attributed to the poor access to quality seeds (Coulibaly et al., 2020); this alone could determine up to 40% of crop productivity (Ilieva et al., 2013; Achigan-Dako et al., 2014). Because of its orphan nature, farmers face challenges accessing *M. geocarpum* quality seeds. Providing high-yielding and quality seeds of *Macrotyloma geocarpum* to farmers will help contribute to the improvement of the household incomes through higher crop productivity. Farmers usually rely on low-performing seeds, obtained from previous harvests (Almekinders and Elings, 2001), and consequently end up with very low yields. In an attempt to understand how willing *Macrotyloma geocarpum* farmers are to adopt high-yielding improved seeds, this study modelled smallholder farmers' willingness to pay for improved *Macrotyloma geocarpum* seeds in the Republic of Benin and Togo by assessing trait preferences by farmers, the determinants of their willingness to pay (WTP), and the amount of money they are willing to pay for improved *doyi* seeds. Our results will enable breeding programs or seed companies to better understand adoption of improved *doyi* varieties by farmers. Understanding farmers' WTP before initiating a breeding program has the potential to help gauge the likely profitability of implementing a breeding program, an aspect often overlooked in orphan crops pre-breeding. We hypothesized that farmers' socio-demographic characteristics, current farm characteristics including farm size, and revenues are likely to affect their willingness to pay for improved *doyi* seeds.

Previous studies of Kersting's groundnut evaluated farmers' knowledge of the production and utilization of the species (Akohoué et al., 2019; Coulibaly et al., 2020; Kafoutchoni et al., 2022; Toure et al., 2022) and highlighted the importance of developing a research program focused on cultivar improvement. However, the success of a plant breeding program depends on the extent to which a released variety is adopted. Hence, unravelling factors shaping adoption of genetic innovation by end-users is key to improving crop productivity. In this study, statistical models were combined to model farmers' willingness and the extent of their willingness to pay for improved *M. geocarpum* seeds.

2. Agricultural extensions services and factors affecting seed adoption and willingness to pay

In Africa, farmers have different levels of access to agricultural extension services as a result of the various efforts of the Government, non-governmental organizations, and private companies. Extension services in agriculture are supposed to contribute to and have a great impact on the incomes of farmers (Cunguara and Darnhofer, 2011), which basically are characterized by low income attributed to the subsistence nature of their farming system. Access to quality agricultural extension services can play a tremendous role in increasing food production and ensuring food security in Africa as witnessed in the case of maize improved varieties which contributed to increase household food security in South Africa (Sinyolo, 2020).

The willingness of farmers to pay for extension services can depend on several factors including the severity of the problem which the extension services will solve as well as the economic return of the services (Singh and Narain, 2016). Many methods are used to analyze the WTP for technology adoption in agriculture including the stated preference, fixed methods (Waldman et al., 2014; Channa et al., 2019), Becker De-Groot-Marschack (BDM), and auction (Cole et al., 2020).

Studies conducted on agricultural technology adoption revealed that adoption of improved varieties in Africa exhibited a positive impact on food and nutritional security (Ochieng et al., 2019; Sinyolo, 2020). In the Democratic Republic of Congo, many factors were reported to determine decision making for improved potato variety adoption. Among them are the age and the distance between house and field, which are negatively correlated with the decision to adopt improved potato varieties, whereas factors like small farm size, the education level of farmers, income, cooperative membership, and access to extension services positively correlated with the decision to pay (Mugumaarhahama et al., 2021). In Ghana, rice technology adoption intensity was shaped by gender, age, and number of adults in the household, the latter emphasizing the availability of labor (Addison et al., 2022). Other factors like access to finance to support activities, farm size characteristics, and household income also affect climate smart agriculture technology adoption including improved seeds (Andati et al., 2022). Likewise, Ullah et al. (2018) reported that socio-demographic factors such as farmers' age, farm size, household size, education levels, experience, extension service, and credit access as well as climatic factors affect farmers' willingness to adopt improved peach cultivars. Under climate variation, smart adaptation strategies are needed for agricultural development. In Pakistan, climate change adaptation strategies are supported by many factors including farmers education, the family and farm size, and climate characteristics (Ali et al., 2020).

3. Materials and methods

3.1. Study area and respondents' sampling

The study was carried out from June to October 2019 in the Northern Guinea Zone of Benin and Southern Sudanian Zone of Benin and Togo (Figure 1), two suitable production areas of Kersting's groundnut in West Africa according to Coulibaly et al. (2022).

Villages that produce *doyi* were selected based on production areas previously identify by Akohoué et al. (2019) while respondents were selected using a snowball technique in each zone. Also known as the chain referral sampling method, the snowball technique is a widely used approach for intentional selection of expert informants, which in our case are the farmers who are cropping or who have cropped at least once in their lifetime Kersting's groundnut. Briefly, as part of this method, we went to the study sites and sought in each community an informant that is culturally competent (Kersting's groundnut farmers) regarding the production of Kersting's groundnut; they would then bestow upon others a similar competence, repeating the process from new participants progressively until the desired respondents sample size of local experts in the community is completely covered. This respondent selection approach led to a result of 3 villages (with 30 *doyi* producers) in Togo and 77 villages in Benin (with 537 *doyi* producers). The three villages in Togo included Pimimi, Nadoba, and Matema. Example of villages of higher number of producers in Benin included Gounoukouin, Kingni, Agouna, Sovlegni, Kemondji, Sowiandji, and Thio.

The Northern Guinean Zone, located in south of the Sudanian Zone, is covered by a semi deciduous forest with tall trees. Its average rainfall varies from 1,200 to 2,200 mm per year, and it experiences a long drying season that can last up to 7 or 8 months. The Southern Sudanian Zone is characterized by one rainy season with an annual rainfall ranging from 600 to 1,200 mm per year and a temperature ranging from 21 to 35°C daily. The Southern Sudanian Zone's vegetation is mainly made up of woodlands, savannas, and gallery forests. This zone is characterized by a unimodal rainfall pattern with one rain season and one dry season. The Southern Sudanian Zone is considered as a transition zone between the Sudanian and Guinean zones with wooded savannas.[1]

3.2. Data collection

After the enumerator got respondents' consent, the interview was then carried on using a semi structured questionnaire. The data collected included information on the respondents' socio-demographic characteristics, knowledge of the crop (cropping zones the last 3 years, production data, utilization, and constraints in the production), the number of cultivars they know and their perception of the crop cultivation (depletion and factors that favor that depletion in the area), and the different use categories of the crop (food, sales, medicinal, and cultural uses) in each community. The economic value of the crop, which was measured using its market value at sowing, was also recorded. As for the willingness to pay, the method of willingness to pay used during the study was the stated preference question type with dichotomous choice contingent valuation methods (Breidert et al., 2006; Huffman and McCluskey, 2017). Data on the amount farmers were willing to pay were also collected in two ways. The first method was direct by asking farmers to fix the maximum and minimum amount that they would freely pay for improved *M. geocarpum* seeds. Secondly the willingness of farmers to pay was evaluated by using indirect survey techniques. At this stage, respondents were provided a range of some bid amounts fixed by a seed enterprise to sell 1 kg of improved *doyi* variety. Those amounts fixed by the seed enterprise varied from USD 13.23 (XOF 8000) to USD 1.15 (XOF 700), see detail in Supplementary Table 1. The willingness to pay or not for the improved variety started with the highest amount; the responses of farmers were recorded as yes or no. The value of the amount that farmers were willing to pay was identified by checking the maximum bid the farmers accept to have access to the seeds. Farmers who did not intend to buy improved seeds were attributed a value of USD 0.

Quantitative data (agricultural income, farm size, total income, revenue from *doyi* production, expected yield of improved varieties,

1 https://eros.usgs.gov/westafrica/node/147

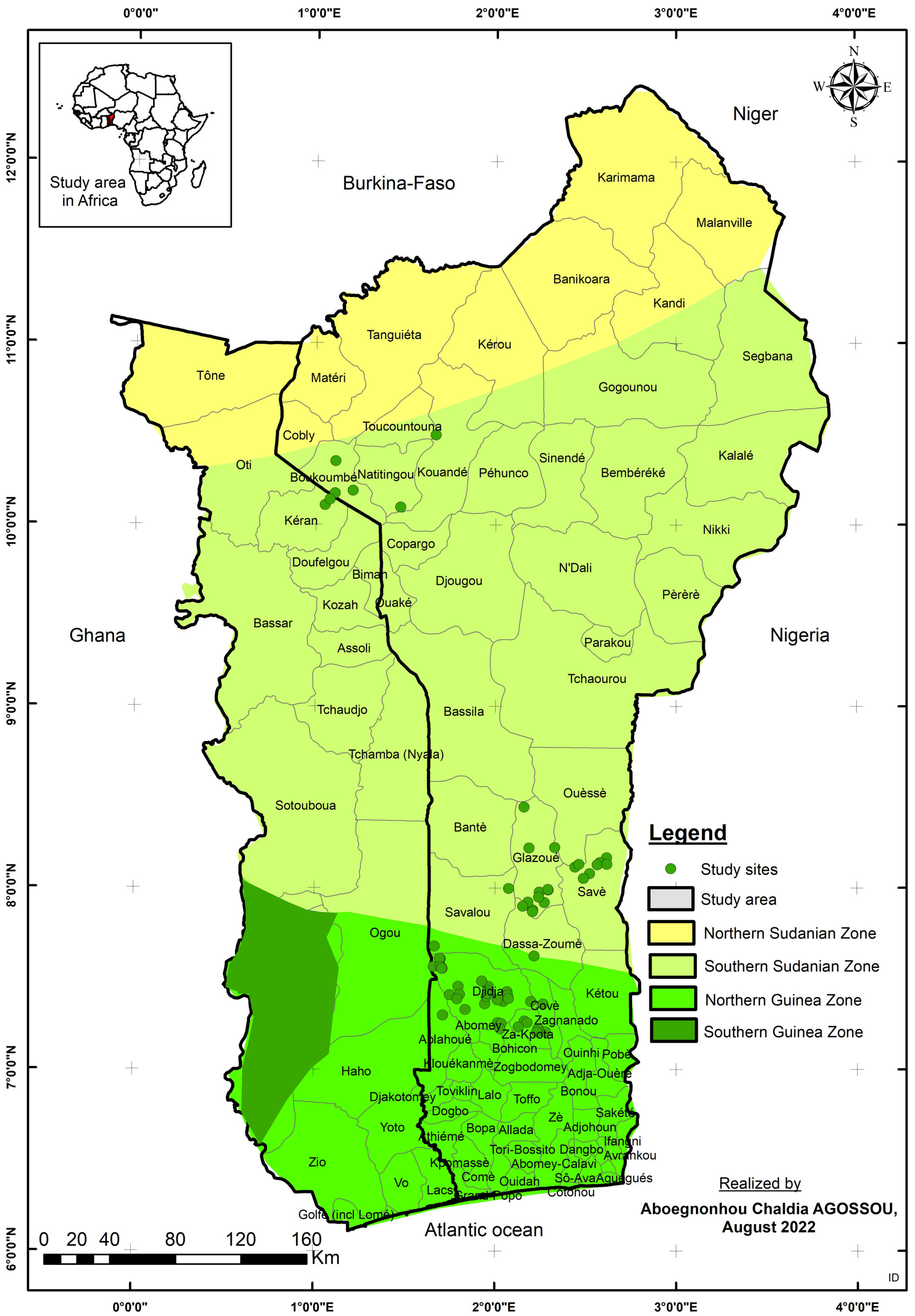

FIGURE 1
Map showing the study area.

experience in the *doyi* production, and household size) and qualitative data (access to agriculture extension services, nutritional quality of seeds, seed type, origin of seed used, availability of labor, degree of adoption of new varieties or technologies in agriculture, availability of agricultural inputs, and access to market to sale farm products) were also collected. The degree of adoption of new varieties was explained in four modalities: early adoption (when farmers adopted the seed at its initial stage), middle adoption (adopted the innovation before majority of the community people), late adoption (adopted the innovation after majority of the community people adopted it), and no adoption (when farmers prefer to use local landraces or practices).

3.3. Statistical analysis methods

All analyses were performed in R version 3.6.1 (Team RC, 2019). Descriptive statistics (mean, standard error, and frequency) were used for socio-economic and demographic data. A Spearman correlation analysis was used to test the relationship between variables while a Kruskal-Wallis, analysis of variance, Wilcoxon-test, and *t*-test (where necessary) were used to compare means of variables like agricultural income, income from *doyi* production based on the zone of the respondent, gender, and occupation. The economic value was analyzed through the selling price of the seed at sowing times, which was recorded per zone for each cultivar. A Spearman correlation analysis was used to test the correlation between the current yield of the crop and the expected yield of an improved variety for which the farmer is willing to pay. Student paired-test statistics were used to compare the freely proposed amount by farmers and the fixed proposed selling price of the seed of improved variety here called amount willing to pay (AWTP).

The explanatory variables included in the regression models were selected after testing the existence of multicollinearity through correlation tests among continuous variables and contingency coefficients. Supplementary Table 2 presents these variables and their *a priori* signs. Spearman correlation analysis was applied for the numerical data, whereas for dummy variables, a contingency coefficients method was used to check the independence between variables through Chi-square and Fisher-exact tests.

Classification trees and linear models estimated via ordinary least squared (OLS) tests were used to analyze the factors that can influence the willingness to pay for the seed. Whereas regression trees, the generalized linear model (glm), and Tobit regression (Tobin, 1958) were used to identify the factors that drove the farmers' amount willing to pay. The amount of deviance accounted by the glm model was calculated by using the Dsquared function of the package modEvA (Barbosa et al., 2016).

For all regression analyses we used the general equation $Y_i = \beta_0 + \beta_1 X_i + \varepsilon i$.

Whereas for the OLS, the Y_i used was the dummy dependent variable, which takes the value 1 if farmers are willing to pay and 0 otherwise. To implement the OLS in R, the command "lm" was used.

For the glm, Y_i was the amount willing to pay for improved seed freely proposed by farmers or fixed by the seed enterprise.

For all regression, β_0 was the intercept, β_1 was a vector of regression coefficients, and X_i was a vector of explanatory variables assumed to be correlated with the dependent variables (here WTP or AWTP). εi was an error associated with each regression.

For the case of the Tobit model, regression was based on the left censored and "vglm" function associated with the package VGAM used for this purpose in R (Yee, 2007).

For each regression model both continuous and categorical variables in Table 1 were initially used, followed by model simplification by elimination of variables. The classification and regression trees (CART) were performed using the ctree function of the "partykit" package in R (Hothorn and Zeileis, 2013) to select the most significant variables.

3.4. Concept clarification

AWTP, or **Amount willing to pay**, was evaluated through two methods: amount fixed by the seed enterprise and amount freely proposed by farmers.

Amount fixed by seed enterprise: This amount is fixed by the seed enterprise in the questionnaire for 1 kg of improved variety of *doyi*. This Amount varies between USD 13.23 and USD 1.15 [exchange rate of 21 April 2020 (1 FCFA for 0.0017 USD)].

Amount freely proposed by farmers: The maximum amount that farmers can allow to acquire 1 kg of improved variety of *doyi* when asked directly.

TABLE 1 Socioeconomic characteristics of respondents.

Characteristics	Modalities	Total	
		Size (*n*)	(%)
Number of respondents	Value	567	100
Number of villages	Value	80	
Sex	Male	379	66.85
	Female	188	33.15
Agro-ecological zones	Southern Sudanian Zone (SSZ)	200	35.27
	Northern Guinea Zone (NGZ)	367	64.73
Years in the cultivation of *doyi* (years)	Less than to 20	299	52.74
	20–40	205	36.15
	40–60	63	11.11
	Mean = 19.58		
Age	Below 20	5	0.85
	20–40	212	37.4
	40–60	269	47.45
	60–80	74	13.06
	80–100	7	1.24
	Mean	44	49
Instruction level	Illiterate	416	73.36
	Primary	81	14.28
	Secondary	51	8.99
	High school	13	2.29
	Undergraduate student	6	1.06
Marital status	Single	20	3.53
	Married	530	93.47
	Widowed	17	3
Linguistic group	Gur	65	11.46
	Kwa	430	75.85
	Songhai	2	0.35
	Yoruboid	70	12.34
Number of children in the household	Minimum	0	–
	Average	4	–
	Maximum	15	–
Household size	Minimum	1	–
	Average	8	–
	Maximum	25	–
Main occupation	Others	23	4.06
	Farmers	544	95.94
Migration	Native	433	76.36
	Migrant	134	23.63

4. Results

4.1. Socio-economic characteristic of respondents

A total of 567 respondents were interviewed in 80 villages across the two zones of the study with 65% of them living in the Northern Guinea zone and 35% of them in the Southern Sudanian zone. Most of the respondents are from Benin. The socio-economic characteristics of these respondents are summarized in Table 1. The typical respondents are 44 years old and is likely to be a man (66%). Most of the respondents did not attend western schools (73.17%) and most were married (93.21%). They had on average of four children and an average household size of eight persons.

The respondents belong to a total of 15 ethnic groups categorized in five different linguistic groups based on the grouping suggested by CENALA (2003). The majority of the respondents (75.85%) spoke Kwa and are from the Fon, Mahi, Agouna, Adja, and Ewe ethnic groups. This is followed by the Yoruboid linguistic group, which represented 12.34% of the respondents and included ethnic groups such as Idatcha, Tcharbè (Nagot), and Yoruba from Republic of Benin. Next, 11.46% of the respondents were from the Gur linguistic group, which includes the ethnic groups Ditammari, Obiaro, Yom, Temberma, and Warma. The Songhai linguistic group represents 0.35% of the respondents and includes the Dendi ethnic group.

4.2. Economic value of the crop in relation to cultivars and ecological zones

Most of the respondents (90.63%) who engaged in *M. geocarpum* production cultivated the white-seeded cultivars called doyiwé (*white doyi*) in the Fon and Mahi languages. Those two socio-linguistic groups that belong to the Kwa-linguistic group also referred to the species as doyikoun (literally meaning underground cowpea). The Idaasha and Tcharbè socio-linguistic groups from the Yoruboid linguistic group call the species Atchaka (High economic and nutritional legume), whereas Yoruba respondents call it Oyèyè. The Gur linguistic group use the names Issagnanré or Issanganané to identify the crop. The colored cultivars were found to be cultivated by few farmers (less than 10% of respondents) mostly in the Southern Sudanian Zone. Colored cultivars (Figure 2) included the white-seeded red-eye cultivars (WRC), the red-seeded cultivars (RSC) called *doyi-vovo*, the black-seeded cultivars (BSC) called *doyi-wiwi*, and the white-seeded black-eye cultivars (WBC), the latter being the most cultivated among the colored cultivars. All the existing cultivars are landraces, with the white, red, and black types cultivated in Northern Guinea whereas all five types are cultivated in the Southern Sudanian Zone. The comparison among the estimated seed yield of the five landraces by farmers did not show any significant difference ($p = 0.56$), and the estimated yield averages 480.2 $kg.ha^{-1}$.

There was a highly significant difference among the selling prices of different cultivars ($p < 0.0001$, df = 4, Kruskal-Wallis chi-squared = 102.76). The most economically valued cultivar by farmers was the white-seeded cultivar, which was also the most preferred by consumers. It cost 2.52 ± 0.058 USD in the Southern Sudanian Zone and 2.67 ± 0.031 USD in the Northern Guinea Zone with an average amount of 2.63 ± 0.028 USD. Other cultivars cost 1.65 ± 00 USD for the WRC, 1.72 ± 0.35 USD for WBC, 1.54 ± 0.109 USD for RSC, and 1.53 ± 0.076 USD for BSC.

4.3. Total agricultural and *doyi* revenues

The different types of incomes estimated by farmers (total agricultural and *doyi* incomes) varied significantly among respondents (Figures 3A–I). The average total income and agricultural income were USD 1,327 ± 72.63 and USD 1,171 ± 68.01, respectively. The income from *doyi* production represents about 17% of the total income of farmers with an average amount of USD 232 ± 12.41, which reached 3,308 USD for large-scale producers. Incomes were affected by gender (Figure 3A, W = 51,037; Figure 3D, 52,692; Figure 3G; W = 51,253) and agroecological zone (Figure 3F, W = 40,658; Figure 3I, W = 45,716). The average income provided by *doyi* to men was USD 282.09 ± 17.21 and USD 131.03 ± 10.82 for women (Figure 3G). The trend was the same for the agricultural income (Figure 3D) and total income (Figure 3A), which were higher for men than women. Farmers in the Northern Guinea Zone had the highest income (USD 246.32 ± 14.21) from the cultivation of *doyi* compared to the farmers of the Southern Sudanian Zone (206.49 ± 23.73 USD) (Figure 3I). Occupation was not found to have an effect on the incomes (Figures 3B,H) except for agricultural income (Figure 3E; df = 1, W = 8,087), which showed a significant difference with a higher average income of USD 1,191.88 ± 70.44 for farmers versus USD 700.28 ± 161.90 for other workers with farming as a secondary activity.

4.4. Dynamics and constraints for *doyi* production and perception of farmers of genetic erosion of the crop in the production systems

Table 2 shows that 67.78% of *doyi* farmers did not access agricultural extension services. Those who had access to extension services have it for a few major or staple crops like cotton, maize, and soybean. Farmers' knowledge about the cultivation of *doyi* was transmitted to them by their parents in 96.51% of cases. About 75.26% of the respondents produced the crop in the 2018 cropping season. Relative to the adoption rate of improved technology in agriculture, 48.95% of the respondents declared adopting it in early stages and 39.02% were in the category of middle-stage adoption. Only 3.31% declared they avoid changing practices and did not adopt new technologies or practices and preferred to use traditional knowledge.

About 17% of the respondents abandoned the cultivation of *doyi* due to some constraints (Figure 4), and the majority of the farmers thought that the cultivation area is declining and this favored depletion and even disappearance of the crop (Figure 4B) in some areas.

A total of 11 reasons were recorded as causes for the abandonment of the cultivation of the crop according to respondents. The three most important bottlenecks were (i) the poor quality of seed resulting in a low yield, which was estimated to be less than 500 $kg.ha^{-1}$; (ii) the high labor requirements and the age of farmers (mostly older people); and (iii) the difficulty to access the seed mostly due to the increasing cost of the grains at sowing time. The most important reasons for depletion include low productivity of the existing cultivars and low access to quality seed. Biotic and abiotic stresses impacting the productivity of

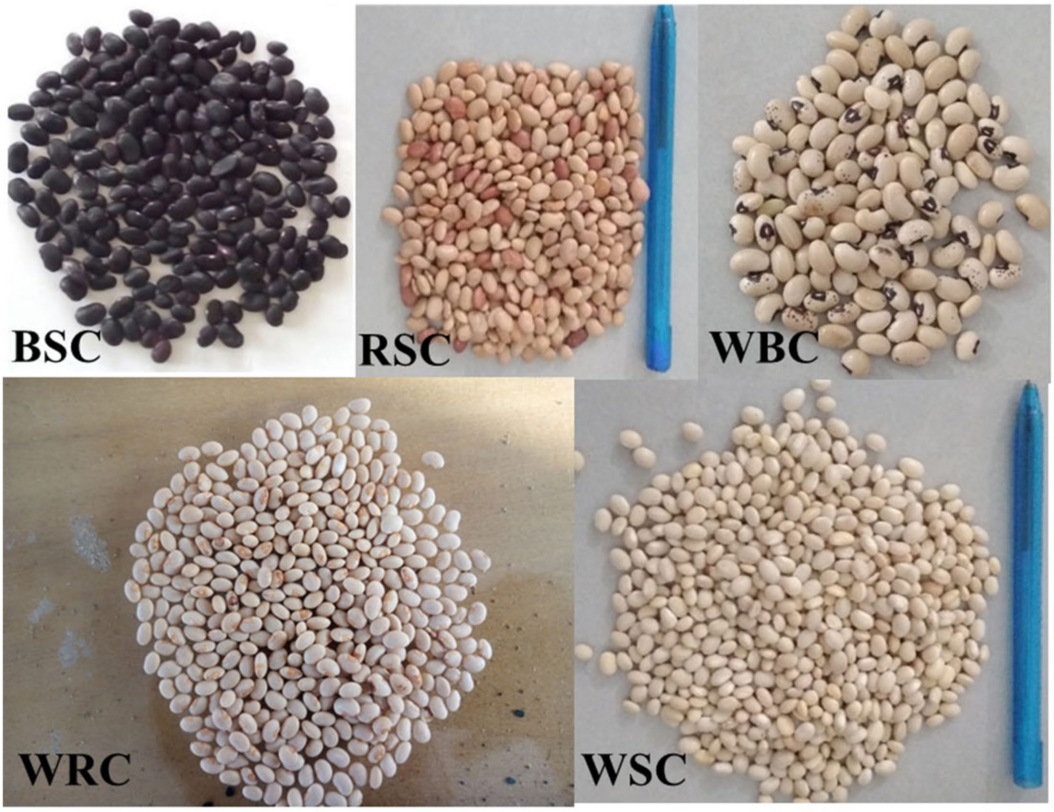

FIGURE 2
Various *Macrotyloma geocarpum* cultivars recorded in this study. BSC, Black seeded cutivars; RSC, Red seeded cultivars; WBC, White seeded with black eyes cultivars, WRC, White seeded with red eyes cultivars, WSC, White seeded cultivars.

doyi also promoted the decrease of the acreage farmers allocated to the crop and their decision to continue the cultivation of *doyi* or not. In the Sudano-guinean zone, the introduction of some competing crops like cotton and soybean, which are cultivated at the same time as *doyi*, also contributed to the crop's decreased production. Farmers' technical constraints in *doyi* production included harvest bottlenecks, high labor, and the fungal impact through seed and rot pod that can reduce the yield which was low naturally.

Many farmers have abandoned the cultivation after having lost their production due to abiotic stress factors like drought and flooding or biotic stress factors like pests and insect disease. It was only in the Djidja district that the transhumance was indicated to be a factor motivating farmers to stop the production of the crop. In the Sudano-guinean area, some farmers attributed the abandonment of the cultivation to the non-existence of fallow land in the area at the time. It seemed like un-fallowed land is not well suitable to produce *Macrotyloma geocarpum*. Despite all those constraints, 92.33% of the respondents that previously abandoned the crop were willing to restart its cultivation if the major constraints related to the low yield, access to quality seed, and sowing time on each type of land were solved.

4.5. Kersting's groundnut seed sources

Kersting's groundnut farmers got access to seeds via an informal seed system marked through three options: saving from previous harvests, purchase from a market, and seed exchange among farmers. Seed saving from previous harvests was practiced by 53.31% of respondents. According to farmers, they have difficulty maintaining the viability of the seed and protect it against post-harvest insects during storage, and they sell all their harvest after production to avoid loss. Seed purchases from markets occurred in 25.78% of cases with farmers going back to markets to buy their own production grain from sellers at sowing time. In this case, they have the option to pay directly to the seller or pay after harvest. They may also have a verbal contract with the seed seller and exchange part of their harvest with that person in November/December during harvest time. Seed exchange among farmers was observed with 1.4% of the respondent and was noticed in the Southern Sudanian Zone. About 18.81% of respondents not only saved their own grains but also went back to market to compete for seed needs if necessary.

4.6. Willingness to pay for improved *doyi* seeds and seed renewal rates

Most of the interviewed farmers (91.90%) were willing to pay for the improved seed of *Macrotyloma geocarpum*: of these, only 23.24% intended to renew the improved seed yearly, whereas 57.22% wanted to renew it just one time. About 11.44% of the respondents agreed to buy the improved seed at an interval of 3 years to renew their seeds every 3 years to ensure high yield.

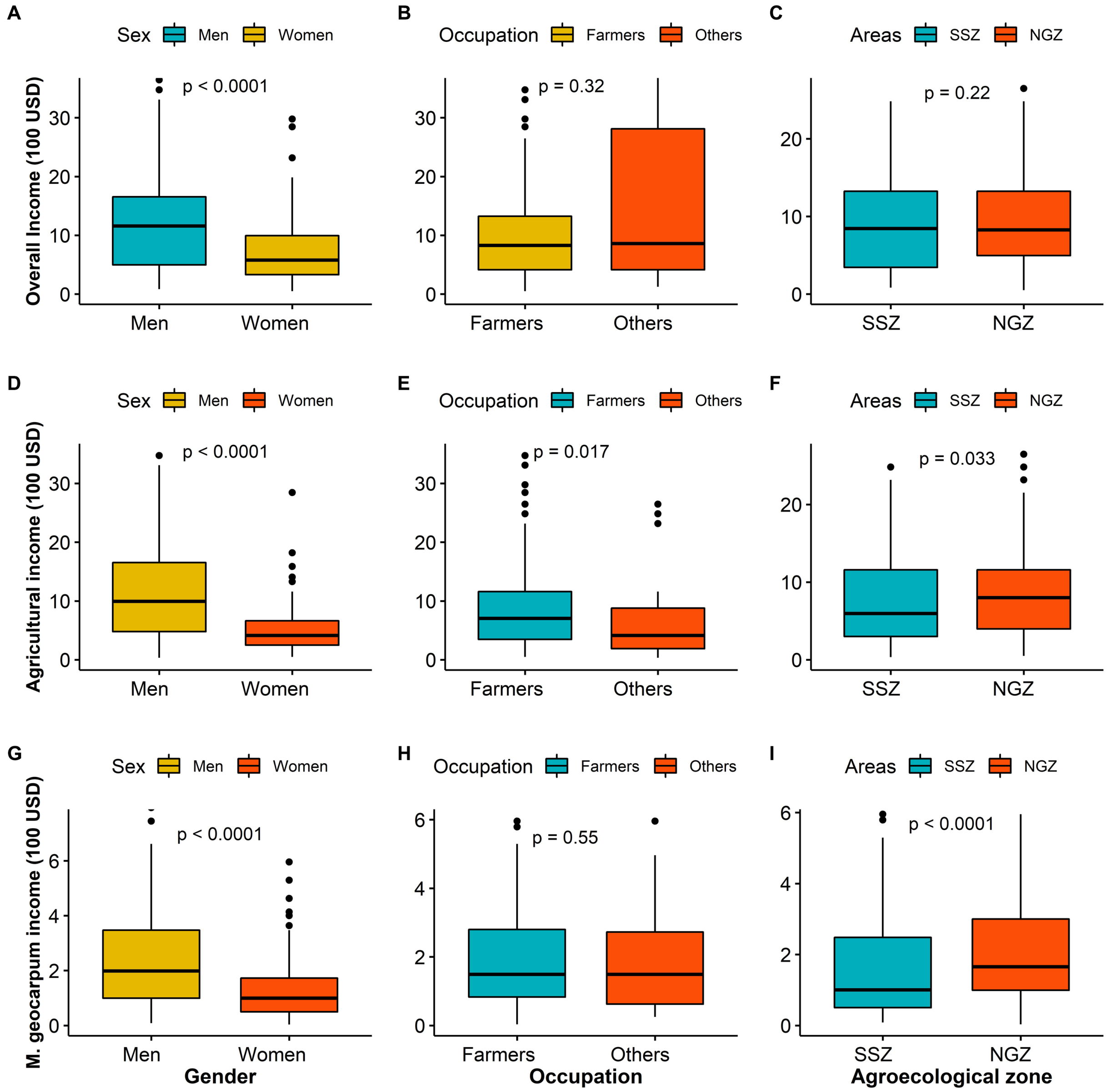

FIGURE 3
Total, agricultural, and *doyi* income earned by farmers in the survey areas. NGZ, Northern Guinea Zone; SSZ, Southern Sudanian Zone. **(A)** Overall income affected by gender; **(B)** Overall income affected by occupation; **(C)** Overall income affected by agroecological areas; **(D)** Agricultural income affected by gender; **(E)** Agricultural income affected by occupation; **(F)** Agricultural income affected by agroecological areas; **(G)** M. geocarpum income affected by gender; **(H)** M. geocarpum income affected by occupation; **(I)** M. geocarpum income affected by agroecological areas.

4.6.1. Factors determining the willingness to pay for the improved seed

By order of descending importance, the adoption level, the experience in *doyi* cultivation, and the cultivar type were the key factors out of the 14 tested variables that determined farmers' decision to pay for the seeds (Figure 5). The most influential factor is the adoption level. It explained with 100% confidence the willingness to pay for improved seed by a non-adopter and late-adopter farmers ($p = 0.027$).

Unsurprisingly, farmers with no adoption level were less willing to pay for improved seeds compared with later-stage adoption famers. For the middle-stage and early-stage adoption famers, the decision to pay was conditioned by their experience in the crop cultivation and the type of cultivar produced. Farmers' willingness to pay was at its highest level in less experienced farmers opting for the BSC, RSC, WRC, and WSC cultivars. In parallel, farmers with more than 52 years of experience in *doyi* production were less willing to pay for improved seed compared with their counterparts of <52 years of experience; those farmers opted for the WBC cultivar.

Based on the ordinary least squared method (Table 3) the WTP was affected by the estimated landrace yield, expected yield of the improved varieties, the income from the cultivation of the crop, and the adoption level of technologies. The result showed that the willingness to pay for improved seed was positively affected by the expected yield, the income from the crop and the middle-stage adoption level.

TABLE 2 Characteristics related to *doyi* production by respondents.

Variables	Modality	Unit	Frequency (%)
Decision about *doyi* production in the household	Production in the last season	% of yes	75.26
	Abandonment of the *doyi* cultivation	% of yes	16.9
	Planting in the future	% of yes	92.33
Access to agricultural extension services	Access to agricultural extension services	% of yes	32.62
Adoption level	No adoption	% of yes	3.35
	Late adoption	% of yes	8.3
	Middle adoption	% of yes	39.32
	Early adoption	% of yes	49.03
Knowledge on *doyi* transmission channel	Generation to generation	% of yes	96.51
	Neighbors	% of yes	3.49

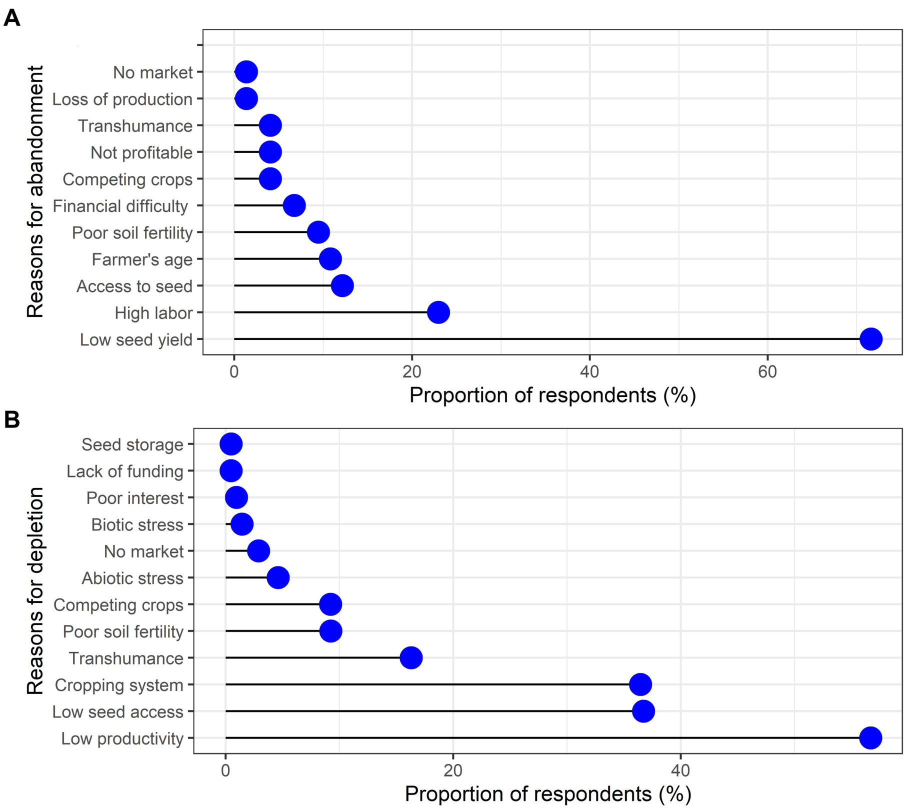

FIGURE 4
Abandonment **(A)** and depletion **(B)** factors of *M. geocarpum* production in Benin and Togo.

Conversely, the willingness to pay was negatively influenced by the farmers' current yield and the absence or the late adoption level. The coefficients for the variables were statistically significant (Table 3).

Both the classification tree model and the Logit regression model clearly concurred on the adoption level of technologies as the main factor which drove farmers to pay for improved *Macrotyloma* seeds.

4.6.2. Amount willing to pay for 1 kg of *Macrotyloma geocarpum* seed

- Amount freely proposed by farmers to buy 1 kg of improved seed.

The most commercialized cultivar was the white-seeded type in the two zones investigated. Farmers intentionally proposed to pay for that cultivar the amount of 5.2 ± 0.28 USD in SSZ and 4.75 ± 0.14 USD in NGZ. For other cultivars found only in SSZ, farmers proposed to spend for each kg of improved varieties the amount of 2.20 ± 0.27 USD, 2.04 ± 0.106 USD, and 1.68 ± 0.098 USD for the red-seeded, white-seeded with black eyes, and black-seeded cultivar, respectively. The significant difference was revealed among those proposed amount within the Southern Sudanian Zone ($p < 0.0001$; df = 4; Kruskal-Wallis chi-squared = 68.341).

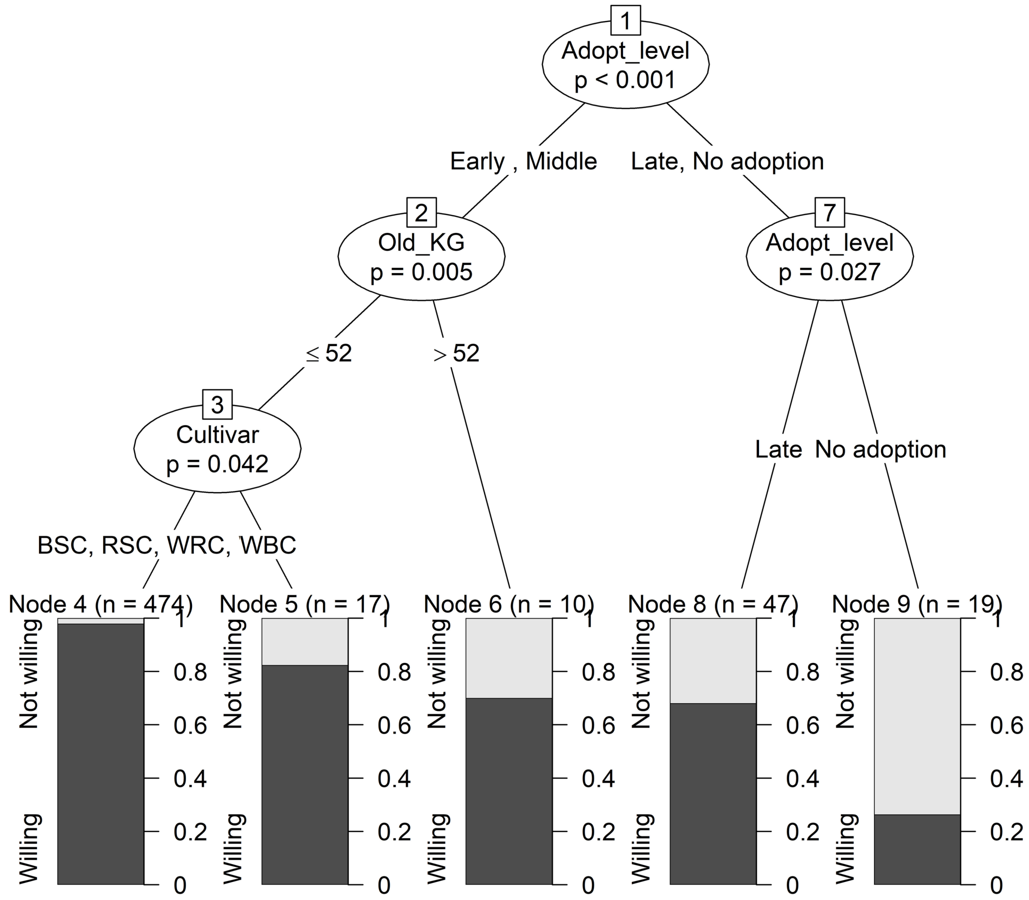

FIGURE 5
Classification tree showing the factors affecting the willingness to pay for *M. geocarpum* seed.

TABLE 3 Factors affecting willingness to pay (WTP) through linear model estimated via ordinary least squares.

WTP	Coef.	Std err.	*t* value	*p* > |*t*|
Constant	1.007e+00***	4.057–02	24.817	< 0.0001
Estimated yield	−1.168e-03***	8.818e-05	−13.249	< 0.0001
Expected yield	4.634e-04***	1.890e-05	24.523	< 0.0001
Income from *M. geocarpum*	6.616e-05**	2.259e-05	2.929	< 0.01
Adoption level: late	−9.485e-02***	2.628e-02	−3.609	< 0.001
Adoption level: middle	7.791e-03^{ns}	1.427e-02	0.546	0.58
Adoption level: no adoption	−3.270e-01***	4.078e-02	−8.019	< 0.0001
Multiple *R*-squared	0.665			
Adjusted *R*-squared	0.662			

***$p < 0.001$; **$p < 0.01$, ns, non significant.

- Amount fixed by seed companies for 1 kg of *M. geocarpum* seed.

Most of the farmers agreed to pay an amount between 3.309 USD and 8.27 USD. Less than 6% of respondents were willing to pay the maximum amount fixed (13.23 USD) for the improved *doyi* seed. Farmers were willing to pay variable prices for the different cultivars. An average of USD 1.68 ± 0.09 was indicated for the black-seeded cultivars and 2.55 ± 0.39 USD for the white-seeded with black eyes cultivars mostly cultivated in Southern Sudanian Zone. The average amount that farmers were willing to pay for the white-seeded cultivars was 5.65 ± 0.12 USD, whereas the red-seeded cultivars had the lowest price, 2.20 ± 0.27 USD.

The amount farmers were willing to pay differed significantly following the respondent's occupation ($p = 0.033$; W = 7,225) and highly significantly for agro-ecological zone ($p < 0.001$; W = 39,273), the sex of respondents ($p < 0.001$; W = 38,435), and the cultivars ($p < 0.001$; Kruskal-Wallis chi-squared = 101.14; df = 4) (Figure 5). The Northern Guinea Zone farmers were willing to pay a higher price

TABLE 4 Drivers for farmers' decision to pay for improved seed of *doyi* using GLM.

	Freely proposed amount by farmers				Fixed amount by seed enterprise			
	Coef.	Std err.	*t* value	*p* > |*t*|	Coef.	Std err.	*t* value	*p* > |*t*|
Constant	2.7546***	0.7155	3.850	0.0001	3.201***	0.746	4.287	< 0.0001
Sex: Women	−0.8433***	0.2397	−3.517	0.0004	−0.5774*	0.2538	−2.275	0.023
Estimated yield	−0.0108***	0.0016	−6.420	< 0.0001	−0.0084***	0.0017	−4.883	< 0.0001
Expected yield	0.0045***	0.0004	10.479	< 0.0001	0.0034***	0.0004	7.843	< 0.0001
Income from *M. geocarpum*					0.0009*	0.0003	2.463	0.0141
Adoption level: late					−1.4139**	0.4743	−2.981	0.0030
Adoption level: middle					−0.6538**	0.2292	−2.852	0.0045
Adoption level: no adoption					−0.7399^{ns}	1.1512	−0.643	0.5206
Linguistic group Kwa	2.5097***	0.3648	6.879	< 0.0001	2.9307***	0.3818	7.675	< 0.0001
Linguistic group Songhai	2.3383^{ns}	2.4480	0.955	0.3399	1.2797^{ns}	2.4953	0.513	0.6082
Linguistic group Yoruboid	3.1973***	0.4461	7.167	< 0.0001	3.1545***	0.4633	6.808	< 0.0001
Dsquared	0.27				0.27			
Adjusted Dsquared	0.26				0.25			

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; ns, non significant.

(on average 5.69 ± 0.14 USD) for 1 kg of *doyi* compared with their counterparts, the Southern Sudanian Zone farmers, who were willing to pay 4.68 ± 0.22 USD ($p < 0.0001$; df = 1; $t = 9.0021$). While men were willing to pay 5.76 ± 0.15 USD, women proposed the amount of 4.42 ± 0.20 USD.

- Relationship between the amount fixed by the enterprise and freely proposed by farmers and the farmer's preferred mode of payments.

The maximum amount freely proposed by farmers to pay for the seeds was on average USD 4.63 ± per kg of seed and differed significantly from the average amount fixed by the seed enterprise to sell (USD 5.35) their seed ($p < 0.0001$; $t = -9.0021$, df = 521). Three modes of payments were proposed by farmers for the improved seed. About 50.4% of the farmers were willing to pay cash for the seeds once they sell their next harvest based on a contract, whereas 29.2% of them wanted a cash payment at sowing time, and 20.4% wanted to pay the cost of the seed through a contract which allows them to sell their own production to the seed enterprise or their proposed customers. Clearly, farmers face difficulties to afford seeds during sowing time as they may not have budgeted for seeds and may prefer alternative solutions.

4.6.3. Factors influencing the amount farmers are willing to pay for *doyi* seed

- Factors affecting the freely proposed prices by farmers.

The result of GLM applied to the freely proposed amount by farmers to pay for the improved varieties of *M. geocarpum* revealed four factors that significantly ($p < 0.001$) influenced the decision to spend specific amounts to buy improved seed (Table 4). Men were more willing to freely pay a higher price to access quality seed compared to women ($p < 0.0001$; $t = -3.517$). While the current yield negatively affected the amount freely proposed by farmers ($p < 0.0001$; $t = -6.420$), the expected yield from the improved variety rather positively influenced the amount freely proposed by farmers. ($p < 0.0001$; $t = 10.479$). With regards to ethnic groups, the Kwa and Yoruboid linguistic groups were likely to freely pay a higher amount compared to the Gur and Songhai groups (Table 4).

- Factors affecting fixed prices by seed enterprises.

The generalized linear model analysis on the amount willing to pay fixed prices for Kersting groundnut improved seed revealed six factors that significantly affected the respondent decision to allocate any amount for 1 kg of improved seed of *doyi*. Those factors included linguistic group, adoption level, the expected yield of improved varieties, the estimated yield, the income from the crop, and the gender (Table 4). Women were willing to pay less money compared to men. The higher the expected yield of improved varieties, the more farmers wanted to invest to have access to them. Early adopters were also more willing to pay higher prices for seed of improved varieties compared to farmers with late and middle adoption levels ($p < 0.01$, $t = -2.981$). The greater the income that farmers earned from the sale of *doyi*, the higher the amount they are willing to pay to access quality seed.

As revealed in Table 5, the Tobit model suggested that five factors determined the amount farmers were willing to pay: estimated yield of farmer's landraces, expected yield of new varieties, cultivars type, adoption level, and the income from the crop. The expected yield and the income had significant and positive relationships with the amount that farmers were willing to pay. The higher the yield of improved varieties and the income from the crop the more farmers may pay for improved varieties.

The correlation between the predicted and observed values of AWTP is 0.63, indicating that the predicted values share 40% of their variance with the amount farmers were willing to pay.

- Tree-based methods to identify the factors driving farmers' decisions on the amount to pay for seeds of improved varieties.

TABLE 5 Estimated coefficients for significant explanatory variables of amount willing to pay for improved seed with Tobit model regression.

	Coef.	Std err.	Z	$p > \|Z\|$	[95% Conf. Interval]		p value	Wald stat	LogLik	Pr(>Chi)
Constant	2.307**	0.829	2.783	0.005	0.6821	3.9322	< 0.001		−1227.62	< 0.001
Estimated yield	−0.0119***	0.0015	−7.821	< 0.0001	−0.0149	−0.0089	< 0.0001	−8.013	−1258.4	< 0.0001
Expected yield	0.0049***	0.0003	14.753	< 0.0001	0.0043	0.0056	< 0.0001	14.158	−1329.5	< 0.0001
Cultivars RSC	−0.237	1.564	−0.152	0.879	−3.3046	2.8292	0.879	−0.152	−1262.9	< 0.0001
Cultivar WBC	0.553	0.798	0.693	0.488	−1.0115	2.1181	0.488	0.690		
Cultivar WRC	0.245	2.598	0.094	0.924	−4.8479	5.3386	0.924	0.093		
Cultivar WSC	3.562***	0.549	6.484	< 0.0001	2.4855	4.6394	< 0.0001	6.515		
Income from *M. geocarpum*	0.0012***	0.0003	3.487	0.0004	0.0005	0.0019	< 0.001	3.448	−1234.3	< 0.001
Adoption level: late	−1.9238***	0.4347	−4.425	< 0.0001	−2.7759	−1.0717	< 0.001	−4.438	−1,243	< 0.0001
Adoption level: middle	−0.7329**	0.2276	−3.225	0.0014	−1.1784	−0.2874	< 0.001	−3.192		
Adoption level: no adoption	−2.7115*	0.9008	−3.012	0.0028	−1.4759	−0.9472	< 0.001	−3.541		
Sigma	0.900***	0.0315	28.562	< 0.0001	0.8386	0.9622	< 0.0001			
r	0.63									
R-squared	0.40									

Total observation: 568; left-censored from bellow observations: 46; uncensored observation: 522. ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; $p < 0.1$.

The regression tree model revealed that four factors influenced the amount farmers were willing to pay (Figure 6). These factors included the socio-linguistic affiliation of the respondent, the expected yield, income from the crop, and the respondent's adoption level.

The fixed amount the Gur and Songhai linguistic groups, both located in the Southern Sudanian Zone, were willing to pay depended on their current income from the crop. When the income from the crop is greater than 181.98 USD, respondents from the Gur and Songhai socio linguistic groups were willing to pay an average of 4.89 USD versus 2.04 when the income is lower or equal to 181.89 USD. Most Songhai and Gur linguistic group respondents had on average low income (100.37 USD) from the crop compared to the Kwa and Yoruboid socio linguistic groups who earned around 173.98 USD. This can be explained by the fact that the Songhai and Gur respondents are all located in the SSZ where it is noticed that the production is realized using small areas with food dietary diversification as the primary production objective. Conversely, their counterparts Kwa and Yoruboid produced the crop for market purposes and could have over time selected/retained high-yielding genotypes to maximize income. When it comes to the Kwa and Yoruboid linguistic groups, the most important factor determining the fixed amount they were willing to pay was the expected yield from the improved varieties rather than the yield. When this group's expected yield is greater than 1,140 kg.ha^{-1}, they were ready to pay on average USD 6.89. When the expected yield is lower than 1,140 kg.ha^{-1}, the amount that farmers were willing to pay depended on the adoption level with the non-adopter and late-adopter farmers being ready to pay less (USD 3.65) than early- and middle-stage adopters (USD 5.12).

4.6.4. Desired breeding traits for *doyi* improvement

As the farmers intended to buy the improved *doyi* seed, the improvement of the crop should be based on their preferred improvement traits. A total of 15 traits, categorized into breeding traits and agronomic research needs, were listed by farmers (Figure 7). The top five breeding traits were higher seed yield, high fungal resistance, high storage aptitude, high pest resistance, and high nutritional quality, while the top agronomic research needs included identification of crop fertilization schemes, the best sowing date on different type of soils, how to store the seed, and how to maintain good germination. Farmers expected the improved variety to be 1 ton.ha^{-1} against 500 kg. ha^{-1} for current landraces.

With the global challenges of agriculture nowadays (i.e., climate change, genetic diversity erosion, wars, and unrests), it is quite important to target all traits related to yield components improvement and tolerance of the crop to abiotic and biotic stresses. This includes the crop production cycle, which farmers want to be shorter. The normal current crop cycle goes up to 180 days, but farmers long for Kersting's groundnut cultivars with a production cycle of 75 to 90 days to face variations of climate.

5. Discussion

5.1. *Doyi* production, economic value, and contribution to household income

Areas previously described as being the production environments of the species (Akohoué et al., 2019) and favorable areas in the future for the cultivation of the species (Coulibaly et al., 2022) were investigated. Kersting's groundnut cultivation seems to be more intensive in the Sudano-Guinean region of Benin (here shared between the Northern guinea zone and the Southern Sudanian zone) compared to the department of Atacora in the Northern Sudanian zone. Mainly Northern Guinean and Southern Sudanian areas are included in the ecological areas where the crop must be well cultivated. Overall, men predominated in the *doyi* production as revealed by previous observations about the crop in Benin (Akohoué et al., 2019; Kafoutchoni et al., 2022; Vissoh et al., 2023). This fact is contrary to what we observed in Ghana and Burkina-Faso where women

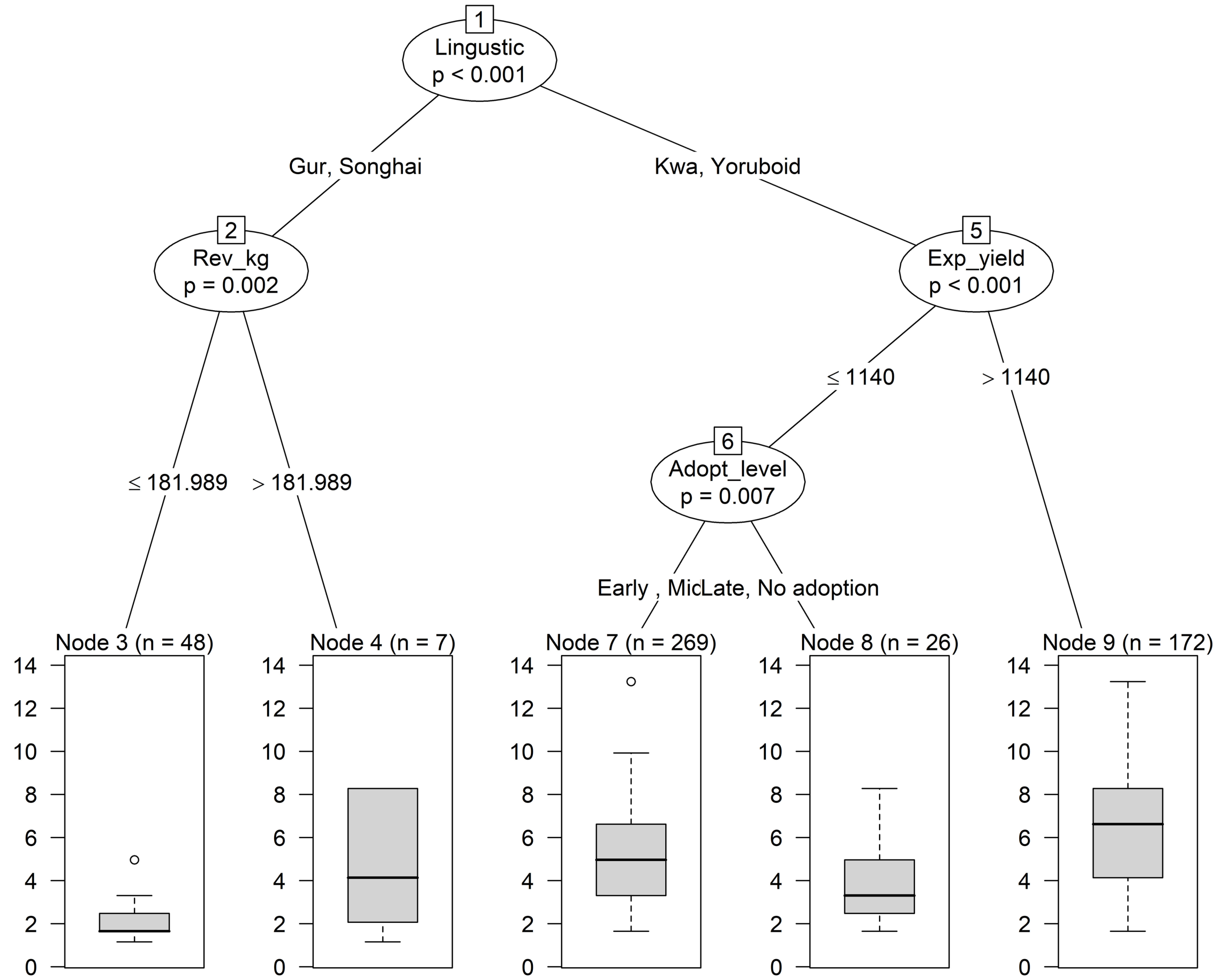

FIGURE 6
Conditional trees on AWTP for 1 kg of improved seed of *M. geocarpum*. MidLate: Middle, Late.

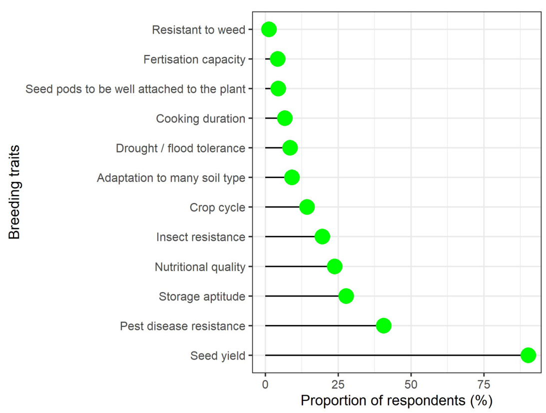

FIGURE 7
Farmers' desired traits for *doyi* crop improvement.

represented the main producers of the crop (Coulibaly et al., 2020). This variation in gender involvement may be linked to specificities in traditional land tenure and to the main objective of the production, which varied across regions and countries. Most women producer have as main objective sustained food security through diet diversification by planting *doyi* in Ghana, Burkina Faso, and the Sudanian area of Benin and Togo, whereas in Northern Guinea the production objective is mainly for income generation. It is also worth pointing out that women by default are part of their husbands' production unit and will not then have their own plot or a large plot unless they have money to hire land or labor for Kersting's groundnut cultivation; they may just cultivate small area for easy management at harvest time to avoid harvest losses because the crop required significant labor (Kafoutchoni et al., 2022).

The selling price of 1 kg of *M. geocarpum* varied considerably from one morphotype to another with the white-seeded cultivars being the most expensive and the most popular variant consumed in Benin. Its average price was 2.6 US (1,500 FCFA) per kg, and nowadays this price is more than the double and can sometimes hike to up to 10 USD. The average prices of other cultivars (RSC, BSC, WRC, and WBC) are less than 2 USD, but the cultivation of those cultivars is mostly for diet diversification. Based on farmers' estimation, the average yield for white cultivars is around 500 kg, which can bring around USD 1200, as reported by Vissoh et al. (2023), but the yield is mostly random according to many farmers due to the genetic potential of the cultivars and the stress during cultivation among other reasons. The average income of Kersting's groundnut of respondents was 232 USD, which is between the 100 and 300 USD previously revealed by Assogba et al. (2016).

Authors are of the opinion that the economic value of the crop is the highest among the grain legumes consumed in Benin. The challenge remains the genetic improvement of the performance of existing cultivars and their stability in appropriate growing areas. Despite the low and uncertain yield, the species' contribution to farmers incomes is relatively high and represents 17% of the agricultural income of producers. In contrast to small farmers, big farmers can get from the crop more than 3,300 USD annually. We found also that the income from the crop is higher for farmers of the Kwa and Yoruboid linguistic group compared to the Songhai and Gur linguistic group who had the lowest revenue from the crop. This can be explained by the fact that all the Songhai and Gur respondents are located in the SSZ where it is noticed that the crop was grown using small areas with food dietary diversification as the primary production objective (Akohoué et al., 2019). Conversely, their counterparts Kwa and Yoruboid, mostly found in the Northern Guinean zone, produced the crop for market purposes. The objective behind the production is explained by the level of income generated by each category of the socio linguistic group.

5.2. Kersting's groundnut production constraints and perception of farmers of genetic erosion

Many production constraints have been revealed by authors (Akohoué et al., 2019; Coulibaly et al., 2020; Kafoutchoni et al., 2022). Among them are the unavailability of quality seeds, the soil infertility, the unavailability of fertilizers for cultivation, transhumance, and the unstable yield; these have gradually contributed to the abandonment of the crop by some growers. With the new results and research focused on the species, there is renewed hope of seeing the sector be better organized and more beneficial for producers. Recently, for instance, it has been proven that the use of amendments based on *Tithonia diversifolia* has improved yield in the Southern Sudanian zone (Anani et al., 2020), thus opening up a route for *doyi* yield increase. The introduction of a new crop like soybean with higher yield and for which the market is very well organized contributed to the abandonment of *doyi* cultivation for some producers. The main production area in Benin is frequently invaded by herders who arrive in the area during the beginning of the dry season (*doyi* harvest time) for livestock feeding. Also, the high labor associate to the crop makes it hard and less attractive as workforces are also moving from production areas to towns, particularly when farmers need the labor force at harvest time.

All those production constraints strongly contributed to the decrease in size of the land allocated to the crop and even the abandonment of *doyi* production by some producers. Fortunately, at the same time, many farmers are trying to be guardians of their genetic resource conservation in different ways including crop regeneration. This has contributed to the fact that all the five cultivars already identified in the area by Akohoué et al. (2019) in Benin and Togo are still found in the production Zone. It proves that the genetic resources of *doyi* are still available even if some are increasingly less cultivated compared to others depending on the areas. So far, the white cultivars are widely cultivated and therefore the least susceptible to genetic erosion whereas other cultivars are much less cultivated. The white-seeded with black eyes, white-seeded with red eyes, and black-seeded cultivars are less cultivated but mostly exist in the upper Southern Sudanian zone. The cultivar most prone to genetic erosion appears to be the white-seeded with red eyes variety, which has been reported to be grown by only one farmer. For this same cultivar, in Ghana, only one sample was collected by Coulibaly et al. (2020) during their survey. This shows that this white-seeded with red eyes cultivar is not widely distributed and not well known by many growers.

5.3. Drivers of farmers' decision to pay for *doyi* seed

In agriculture, the quality of the seed determines the productivity and the income of farmers. Quality seed may always be adopted if it shows superiority over existing varieties or landraces. In the case of the orphan legume *doyi*, any improvement in seed quality will increase the yield and farmer income. So a study of the extent to which agricultural technologies is adopted by farmers is necessary for agricultural development. Adesina and Zinnah (1993) said that the perception of specific technological characteristics explained the adoption decision by farmers. In this paper, the high level of farmers' willingness to pay for the improved varieties were recorded. Indeed, more than 90% of the farmers were willing to pay for improved seeds including farmers who have abandoned the cultivation of the crop.

The factors that affect the willingness and the amount willing to pay for improved seed of Kersting's groundnut were identified. The study revealed that expected yield of improved varieties, linguistic group, adoption level, estimated yield of farmers cultivars, gender, income from Kersting's groundnut, type of cultivars, gender, and experience in the crop cultivation are the main drivers for *doyiwé* farmers to pay for improved seed. Those factors can be categorized into three major groups: socio-economic (gender and linguistic group), farming experience (number of years of experience in *doyi* cultivation, the estimated yield of the crop, and the income), and improved varieties characteristics through the expected yield.

The lower the estimated yield of the crop, the more farmers expect the improved variety to be high yielding and the higher their willingness to pay is. Farmers want the expected yield of the probable new variety of *doyi* to have a grain yield higher than 1,000 $kg.ha^{-1}$ in the farmer's field.

The sociolinguistic group of the respondents is an important factor explaining farmers' decision. Local people from specific sociolinguistic areas develop specific behavior vis-à-vis specific plant genetic resources. Our study shows the Kwa linguistic group, which includes mostly Fon and Mahi ethnic groups, is well involved in *doyi* cultivation. Whatever the location of farmers from the Kwa linguistic group, they produce the crop. This could be attributed to the high economic value of the white-seeded cultivars largely cultivated by those farmers. Farmers were willing to pay more for the white cultivars compare to others. Such a situation is explained by the high demand for the white grain during celebrations at the end of year. Northern Guinean farmers from the Kwa linguistic group placed more importance on the crop and are involved in the cultivation of the crop. The importance of a crop within the sociolinguistic group of each area contributes to the farmers' decision to adopt or not the improved varieties of *doyi*. The years of experience in *doyi* cultivation were positively correlated with the age of respondents, which unfortunately was not among the important determinant of the willingness to pay for *doyi* seed. In contrast, age was directly reported to be an important driver for technology adoption for other crops (Fahad et al., 2018; Ullah et al., 2018). Regarding the experience with *doyi* production, farmers with a few years of experience (young farmers) are likely more willing to pay than older farmers with more experience. This supports the assertion that younger farmers show more willingness to accept and pay for change due to their knowledge relative to new practices (Polson and Spencer, 1991; Boadu et al., 2019). Vissoh et al. (2023) found that with the accumulation of experience years on *doyi*, old farmers may get high yields, and this can explain old farmers' motivations to pay less compared to young farmers who did not have as great a perception of the risk of high prices of inputs, as reported by Fahad et al. (2018). Regarding the adoption rate, which is essential for breeders, farmers defined specific criteria for adopting improved varieties. Those criteria could include the taste of the new variety, nutritional quality, yield potential, and others. These can be well evaluated only when the seeds are released or evaluated in farmer fields.

Both ordinary least square methods and classification and regression trees showed that the income from the crop affects the amount willing to pay for the improved seeds as also reported by Boadu et al. (2019) for Pona certified yam seeds in Ghana and Daniel and Teferi (2015) for agricultural extension services in Eastern Ethiopia. Our analysis shows that women proposed the lowest amount to pay for the improved seed compared to men. Vissoh et al. (2023) showed that gender has a negative impact on the *doyi* yield. This trend was also observed in the Northern Region of Ghana when Banka et al. (2018) evaluated the willingness of farmers to buy legume biofertilizer and revealed that men have greater power to buy legumefix. Additionally, we can pay attention to the objectives of the farming activities of women, which were more oriented to consumption of commodities such as legumes and vegetables.

A gap was found between the freely proposed purchase price by farmers and the fixed amount set by the seed enterprise to sell the improved seeds. The use of direct and indirect survey methods of stated preference to evaluate the amount willing to pay in our study showed that the direct amount proposed by farmers is less than the amount fixed for the quality seed.

5.4. Breeding implication

Seed is the most vital input of agriculture and without a guarantee for quality seeds, other inputs remain worthless. This can explain why farmers stated quality of seed as a primary need. High seed yield and early maturity with resistance to biotic stress (pest and disease) are needed to meet farmers' expectations. The most important among these agronomic traits was the yield potential, which should be greater than 1,000 kg.ha^{-1} against the current cultivars (with a yield less than 500 kg.ha^{-1}). Beyond these criteria, resistance to abiotic stress, such as droughts, should also be considered (Maity and Pramanik, 2013; Hampton et al., 2016). Even if tolerance/resistance to drought was ranked ninth among farmers' desired traits, it is a crucial one that often impedes the top desired trait such as yield. Based on the farmers' preferences, strategies to ensure a consequent seed yield increase in *M. geocarpum* appears to be the next crucial challenge we face.

Recent development in *M. geocarpum* suggested challenges in hybridization in the species (Kafoutchoni et al., 2021), a situation that locks genetic variation creation. Such a bottleneck calls for the necessity to explore alternative diversity generation approaches such as mutation breeding by using physical and chemical mutagens. Moreover, the role of augmenting agronomic practices should not be underestimated, as it holds substantial potential to positively influence crop yield. This includes the implementation of plowing techniques tailored to the unique characteristics of each identified area, a notion previously suggested by Coulibaly et al. (2020).

The aspirations of farmers extend beyond mere improvement of crop performance. Ensuring the enhanced performance of the crop is accompanied by an organized market structure is paramount to guarantee a better profit margin for farmers. Without this, achieving a satisfactory adoption rate of newly released varieties may prove challenging.

6. Conclusion

This study reveals that farmers' purchase decisions for improved varieties are heavily influenced by market availability. Farmers anticipate that new varieties will outperform their current cultivars, with expectations centered around a higher yield of over 1,000 kg.ha^{-1} with higher resistance to fungal pests, which triggers the most substantial challenges to the crop at harvest. Farmers proposed a purchasing price of USD 4.63 per kg of improved seeds while the input-dealers price was around USD 5.35. Farmers willingness to pay is influenced by the anticipated yield of the new variety, the level of adoption, and the income derived from the crop. Additionally, linguistic group membership plays a significant role in the amount farmers are willing to pay. Interestingly, the amount proposed by farmers is significantly lower than the amount they are willing to pay when evaluated against the bid fixed price during the survey, suggesting a propensity among farmers to propose lesser amounts for the same product. As a result, it may be worthwhile to consider additional studies using auction methods to accurately assess farmers' true purchasing capacity for the improved seeds.

Farmers require further education on the benefits of purchasing quality seeds consistently rather than making a one-time purchase, as indicated by 50.4% of respondents. The ongoing practice of saving past harvests for use as seed in the following cropping season also needs to be addressed. It is conceivable that farmers may be sensitive to the price of improved seeds, potentially impacting the adoption rate of future *doyi* varieties. However, if the new product can naturally demonstrate its superiority over local cultivars, a well-devised selling strategy and marketing plan by seed companies in rural areas could lead to its acceptance, increased willingness to pay, and, ultimately, successful adoption.

This study underscores the need for the improvement and development of high-quality *Macrotyloma geocarpum* seeds and their commercialization by seed companies to meet farmers' demands and address issues of seed access and low yield. Once the variety has been developed and released, experimental auction methods could be utilized to gauge farmers' preferences and the amount they would genuinely be willing to pay for the improved seeds.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding authors.

Ethics statement

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. Written informed consent from the participants was not required to participate in this study in accordance with the national legislation and the institutional requirements.

Author contributions

AA and EA-D: conceptualization. AA: investigation, writing and editing, and data analysis. EA-D: validation. EA-D, SN, VF, HO, TK, and MC: review. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

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Methods for assessing the adoption of rice varieties and land use changes in Chitwan, Nepal, using global positioning system transects and focus-group discussions

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Rice varietal adoption was assessed using randomly selected global positioning system (GPS) coordinates in Chitwan district, Nepal. At pre-determined sampling points along the transects, which researchers located using GPS, data were collected on land use and the name of any rice variety grown. These data were then triangulated through focus group discussions (FGD) for each transect. The first two surveys were done in 2005 and 2006 in 14 transects with 440 GPS coordinates representing the major rice-growing areas of Chitwan. Using the same approach, a third survey was conducted in 2022 in 72 out of the 440 GPS coordinates to document rice varietal adoption dynamics over a 16-year period. Farmers had changed the rice varieties they grew, but they continued to grow two to three old-improved varieties that covered more than 40% of the land. Hence, despite large changes in the rice varieties grown, the weighted average age of the varieties over 16 years was not reduced significantly. Despite their lower yields compared with newly released varieties, the older popular varieties persisted as they were in demand by the rice millers, who have little motive to replace rice varieties for which they have an established market. The adoption of rice varieties released in the previous 15 years was low except for Sawa Masuli sub-1, a stress-tolerant rice variety that was adopted in 16% of the study area more than a decade after its official recommendation. This variety had the advantage of having similar grain characteristics to the established variety Sawa Masuli, so millers could easily replace it with the new variety. The study revealed that premium rice lands in Chitwan were replaced with cattle and poultry farms, fishponds, and vegetables. Rice lands with better drainage and close to the Mahendra *Raj Marg* (highway) had been converted into real estate and settlements. There was a good agreement between the data collected from the sampled GPS coordinates and the FGDs. Random selection of GPS coordinates and sampling points is an unbiased, rapid, and efficient method for assessing the adoption of agricultural technologies, varietal dynamics, and changes in natural resources management and land use.

KEYWORDS

adoption, rice, GPS, age of varieties, land use change

1. Introduction

Seeds are the vehicles for transferring new genetic gains to farmers. Adoption of new varieties with better seeds is the most economical way for smallholder farmers to increase yields and profitability, as they do not have to spend more on external inputs. A periodical evaluation of the adoption of new agricultural technologies, such as new varieties, identifies the constraints to their adoption and allows an estimate of the return on investment from agricultural research and development (R&D). Adoption and diffusion of agricultural technologies are expected to help make production systems more productive, profitable, and sustainable (Shang et al., 2021). However, estimating the adoption of technologies, such as the adoption of modern rice varieties, in smallholder-based farming systems is complex and resource-consuming. Consequently, there are few studies on rice varietal adoption, and those that report varietal changes over time are rare. For example, Witcombe et al. (2016a,b) stated that their study was perhaps unique in reporting changes over time.

All estimates of adoption must use some form of survey, either of farmers or of key informants such as seed producers or agricultural extension workers. All are open to bias in the selection of the participants and are then also open to their own biases. Seed production statistics are less open to bias and can be used to easily identify the relative popularity of varieties while demanding fewer resources than household surveys. However, it ignores the considerable areas grown from farm-saved seed (more than 80% in developing countries), all varieties that are not in the official seed production system, and provides little or no information on their distribution in the agricultural landscape.

We are not aware of any prior study that employed GPS to determine a sampling frame to evaluate the adoption and spread of agricultural technologies. We report here on three surveys made over a period of 16 years using GPS-located samples. The rice varieties were grown, and the land use was recorded. The findings from transects were triangulated by means of focus group discussions (FGDs), where groups of local farmers were interviewed.

2. Methods

2.1. Use of the global positioning system

The study district has three major rice-growing areas, namely, eastern, western, and southern Chitwan (Appendix 1; Figure 1). In 2005 and 2006, rice varietal diversity was sampled from 14 transects covering a total of 440 GPS coordinates and 770 sampling points to best represent geographical areas, land types, and rice production ecologies. Out of 440 GPS coordinates, 220 each were allocated to Eastern and Western Chitwan. Southern Chitwan was excluded due to the adverse security situation in 2005. In 2022, 72 GPS coordinates (16% of the total coordinates) from eight out of 14 transects were sampled (Figure 2A).

A baseline sampling frame was established in 2005. Lists of the central points of the transects were prepared by drawing seven-figure random numbers (two for degrees, two for minutes, and three for seconds to one decimal place) using Excel. Only those that fell within the targeted areas were included. The central points of the transects were marked on a topo-map published by the Department of Survey, HMG/Nepal (map not shown). These points were then verified in the field, and non-rice lands such as settlements, forest areas, rivers, irrigation canals, roads, and uplands grown to maize or other crops were excluded and replaced by the next randomly selected point in the list. The coordinates of each point were noted, given the corresponding GPS identification number (a unique identification number), and loaded into an eTrex GARMIN handheld GPS.

Transect Walks were carried out along a 1-km transect. Sampling was done at 100-m intervals, and, in 2005 and 2006, at each interval there were five sampling points (Figure 2B). While deciding the directions of the transect from the central point, non-agricultural areas in the sample were minimized, but to remove bias, there was a pre-decided priority for the direction of the transect, i.e., north, south, east, and then west. Hence, the direction of the study was not always the same (Appendix 2). At each GPS sampling point, the land type (Appendix 3) and the rice variety grown were recorded. In 2005 and 2006, the name of the rice variety grown was determined with the help of the owners or cultivators of the field. In 2022, in addition, each owner or cultivator was interviewed using a checklist to collect additional information, such as the area under the variety and the estimated grain yield per unit area.

In 2022, the sampling along the transect was done at 500-m intervals from the primary point, with three observations taken at each interval (Figure 2B). To compare data from 2006 with 2022, only the 72 GPS coordinates from the same eight transects were considered from both years.

2.2. Focus group discussion

FGD is a simple participatory method, and one FGD was conducted at each transect after the transect walk with the owners or cultivators and their neighbors to collect data for triangulating with those from the transects. In each FGD, there were 15–20 male and female participants. A total of 300 farmers participated in both 2005 and 2006, and 145 in 2022. The participants were decided by the community, but they were advised to have

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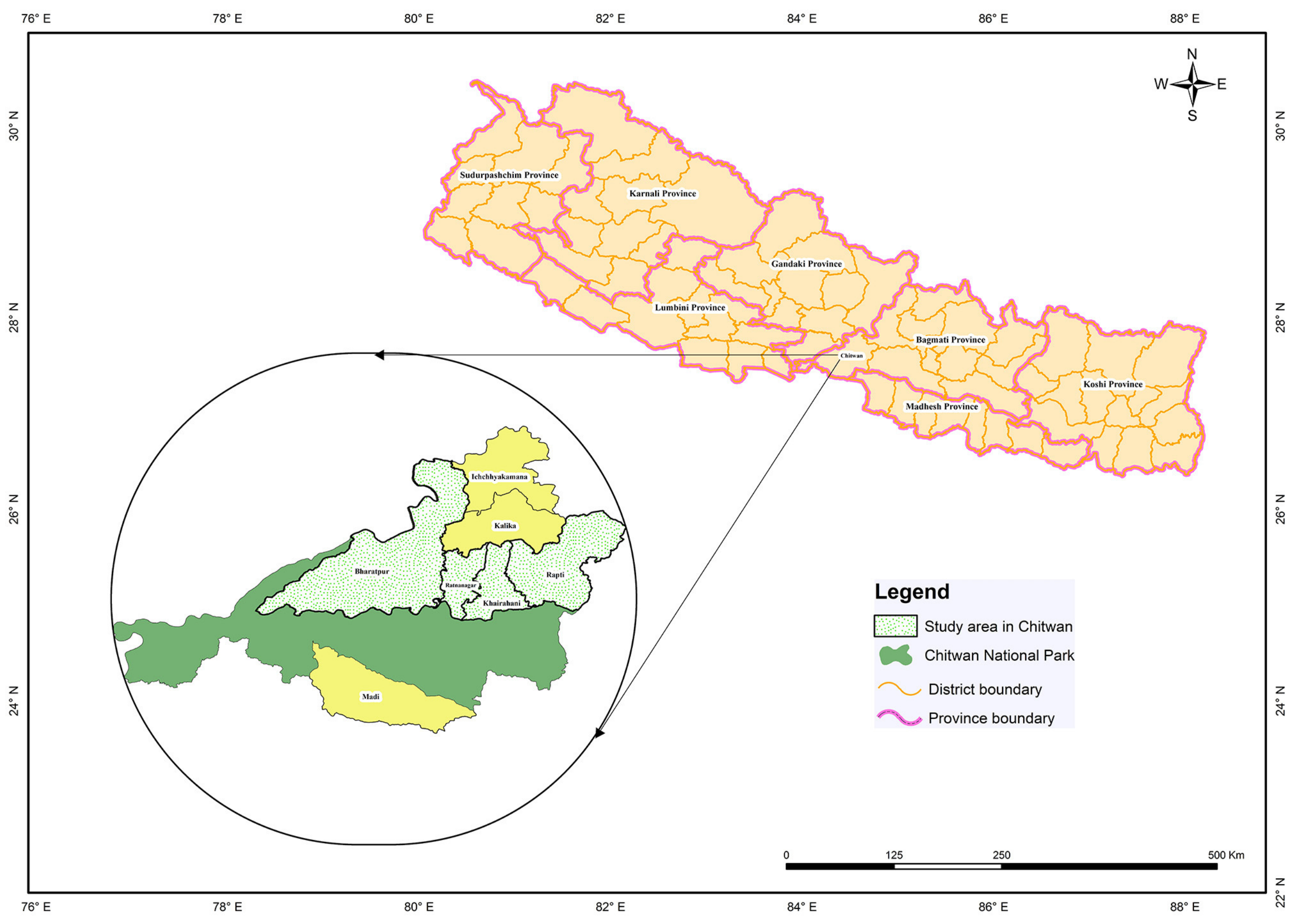

FIGURE 1
Map of Nepal showing the study area in Chitwan district.

knowledgeable farmers of both sexes and that they should try and represent ethnic groups, disadvantaged groups, and youth. In each FGD, 4–5 farmers also participated in the transect walk. The discussions lasted from 1 to 1½ h. The area coverage of each rice variety, their yield, and other benefits were discussed and documented.

2.3. Statistical analysis

Simple statistics such as percentage, average, and weighted average, standard error for the yield of rice varieties, and coefficient of correlation were computed using the data collected in the study. Descriptive analysis was the main analysis used in the study. The frequency of counts of any variety in the transect data would be expected to be directly related to the area on which it is grown. Hence, we consider the frequencies and area percentages to be equivalent. To have clarity about varietal dynamics between 2006 and 2022, rice varieties were classified into the following categories: (i) new improved, (ii) old improved, (iii) new climate resilient, (iv) new unregistered, (v) old unregistered, (vi) hybrids, and (vii) landraces.

3. Findings

3.1. Adoption of rice varieties from 2005 to 2006 in the 14 transects using GPS

The data for 2005 and 2006 indicated distinct year-to-year rice varietal dynamics in the study area. Old-improved varieties dominated the rice production system for both years; interestingly, farmers in 2006 switched to old-improved varieties, which resulted in an area reduction under new-improved varieties (Figure 3). In general, the same rice varieties were identified, but with changes in the frequency of their occurrence. The most striking changes were for rice varieties bred using client-oriented breeding (COB) (from 8 to 3%), Sawa Masuli and hybrids (from 0 to 4%), Masuli (from 24 to 33%), and Radha-4 (from 6 to 3%), while there was no change for Sabitri (Table 1; Figure 3).

3.2. Adoption of rice varieties from 2006 to 2022 in the eight transects from the GPS

The adoption of rice varieties for 72 sampling points from eight transects in 2022 was compared with the same sampling

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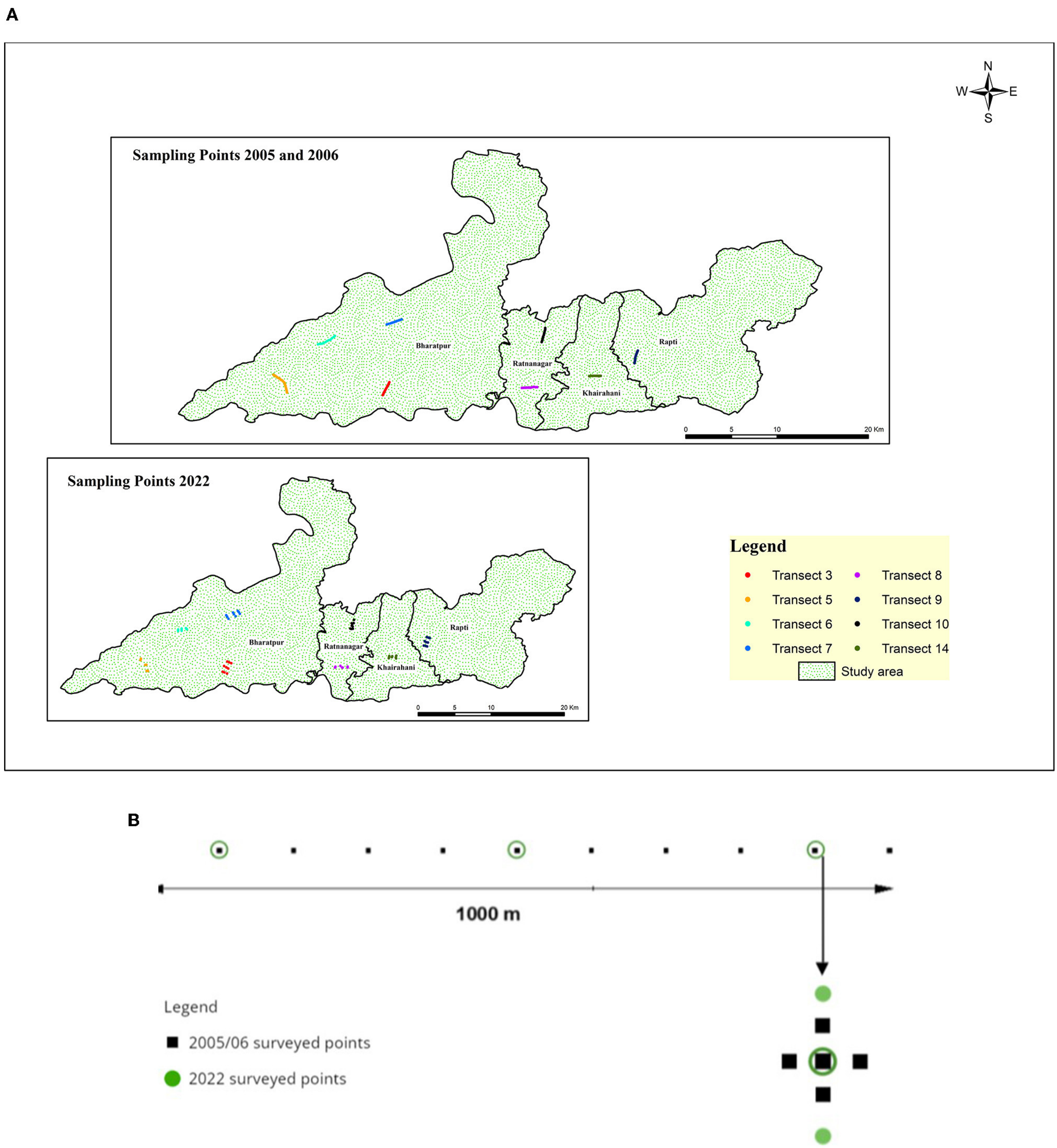

FIGURE 2
(A) Map of the study area in Chitwan, Nepal, showing GPS coordinates for 2005, 2006, and 2022. Four hundred and forty GPS coordinates and 770 sampling points were randomly sampled in 2005 and 2006, while 72 of those were randomly selected and resurveyed in 2022. **(B)** A schematic diagram showing how the survey was done at each sampling point in 2005, 2006, and 2022.

frame for 2005 and 2006. A total of 29 rice varieties were found across the three surveys. Overall, the rice varietal richness had increased, as 19 varieties were recorded in 2022 in the transects compared with 11 in 2005 and 12 in 2006 (Table 1; Appendices 4, 5 in Supplementary material). The area under old-improved varieties decreased to 40% in 2022 from nearly 66% in 2006. Interestingly, old-improved varieties were replaced in large part by unregistered varieties, and a few of those were also quite old rice varieties from India. Interestingly, area under the new improved varieties decreased slightly.

In 2022, three hybrid varieties were identified, whereas, in 2006, hybrid rice varieties were only reported as a category. In 2006,

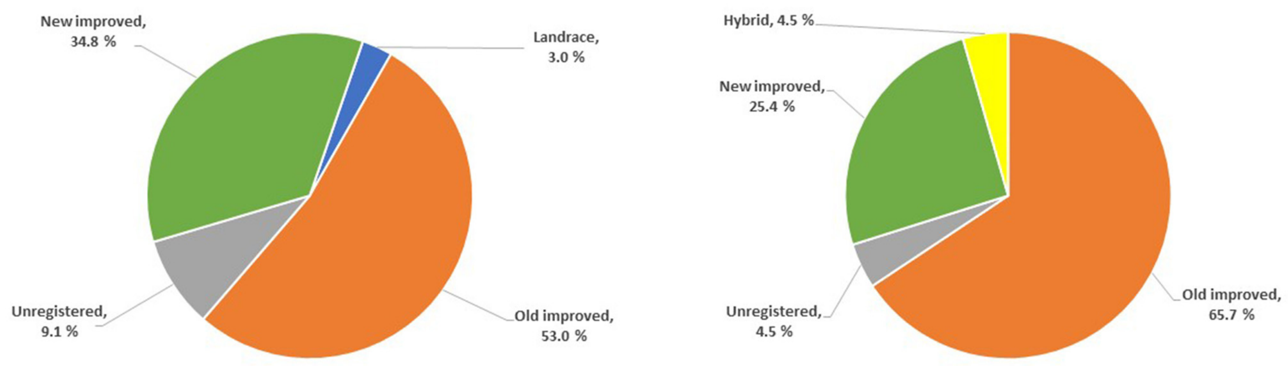

FIGURE 3
Overall rice varietal frequencies (%) across the fourteen transects in 2005 **(left)** and 2006 **(right)** in Chitwan district, Nepal.

hybrids occupied only 4% of the area, and this increased to 7% by 2022 (Table 1; Figure 4; Appendix 1).

A total of 12 inbred varieties grown in the 2022 survey were new as they were not found in 2006, and their ages ranged from 11 to 48 years. The two oldest varieties, namely, Hema (48 years) and Moti (34 years), were recently introduced old varieties from India that are not released in Nepal. In total, 11 varieties grown in 2006 were not found in 2022 (Table 1; Figure 4). Hence, three varieties, namely, Hardinath 1 (3% of area in 2006 to 2% of area in 2022), Ram (12–19%), and Sabitri (28–19%) were cultivated in both years.

3.3. Agreement between the GPS transects and the FGDs

Overall, there was good agreement between the data from the GPS coordinates and sampling points and the FGDs in both the 2006 and 2022 surveys. This was also the case in 2005 (data not shown). The correlations between the areas from the FGDs and the frequencies from the transects were high ($r^2 = 0.89$). The FGDs always gave a higher estimate of the total number of rice varieties grown than were found in the transects (Figure 5).

3.4. Age of rice varieties, grain yield, and adoption lag

The uptake and adoption of more recently released rice varieties was slow, as only two out of 36 rice varieties released between 2006 and 2022 for cultivation in the Nepal Terai (SQCC, 2022) were adopted by farmers (Table 1; Figure 3). These were Sawa Masuli sub-1 and Swarna sub-1, and both were stress-tolerant rice varieties (STRVs) developed by the International Rice Research Institute (IRRI) in the project "Stress-Tolerant Rice Varieties for Africa and South Asia." Sawa Masuli Sub-1 covered 16% of the area, while Swarna Sub-1 covered 4% (Figure 4; Table 1). Several rice varieties grown by farmers were not actually recommended by the seed regulatory system of Nepal, including Malaysia, Katarni, Godawari, Chandan, Gangottari, Hema, Moti, and Panganga (Table 1).

Several of the old-improved varieties that were popular in 2006, such as Masuli (the most popular rice variety in Nepal until early 2000), Sawa Masuli, Makwanpur-1, Kanchhi Masuli, Radha-4, and Radha-11, were not found in the 2022 FGD (Figure 4). The areas under popular varieties Sabitri and Hardinath-1 also decreased.

The average age of cultivars is measured by their age (the number of years since they were released) weighted by the area they cover. Only improved varieties can be included in the calculation because the ages of landraces and traditional cultivars are unknown. The average weighted age of the 19 rice varieties found in the 2022 study was 19.5, which was slightly lower than the 20.6 years found in 2006 (Table 1). The average age is underestimated because of lengthy testing and delays in official release; several of the rice varieties, such as Hardinath 1 and Ram, were released years after their introduction. For example, Hardinath-1 was introduced in Nepal in 1988 and was adopted by farmers, but it was not officially released in Nepal until 2004 (Joshi et al., 2012).

In 2022, nine out of 19 varieties were 7–14 years of age, but the average weighted age was nearly 20 years. High yielding and newly released rice varieties had low adoption; hence, the weighted average age was higher than the average age. The top five varieties occupied most of the land in both years, i.e., 81% in 2006 and 70% in 2022. In 2022, two of these were Ram and Sabitri, which had the lowest yield but covered 19% of the area each (Table 1).

In the FGDs, the participants told the researchers that Sabitri was preferred for its wide adaptation, stable rice yield in varied conditions, and ability to do well even under partially irrigated conditions with moderate application of nutrients. A higher straw yield is another reason for its preference by farmers. Ram is preferred for its good grain quality, softness of cooked rice, adaptability to low input conditions, and fetches good market price. Sawa Masuli, a short-duration variety, is popular for its fine grains, tasty, and softness of rice, and it does well in irrigated conditions. Sawa Masuli sub-1 is preferred over Sabitri because of its higher yield, better taste, and higher market price. Being a late-maturing variety, it is preferred for lowland irrigated conditions. FGD participants also said that hybrid rice varieties are not adopted in larger areas because of high input costs (83% of participants), being highly prone to insect pests and diseases (25%), and a lack of knowledge to confidently invest in hybrid technology (100%).

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TABLE 1 Adoption of rice varieties in eight transects over 72 GPS coordinate in 2005, 2006, and 2022, the age of varieties (*), weighted age, crop duration (*), and yield (**).

Variety	Type of variety	Information on release or registration		Frequency of occurrence			Percentage of occurrence			Age of variety		Weighted age of varieties		Duration (days)*	Yield t/ha**
		Year	Country	2005	2006	2022	2005	2006	2022	2006	2022	2006	2022		
Anadi	Landrace	§	§	2	0	0	3.0	0.0	0.0						
Ankur Jyotika	Pure line	2019	Nepal	0	0	1	0.0	0.0	1.8		3		0.05		
Arize-6444[1]	Hybrid	2011	Nepal	0	0	1	0.0	0.0	1.8		7		0.12	122	5.8
Chandan (CR898-2)[2]	Pure line	2009	India	0	0	5	0.0	0.0	8.8		13		1.14	125–130	4.3
COB	Pure line	2006	Nepal	5	2	0	7.6	3.0	0.0	1		0.03			
Gangotri[2]	Pure line	2011	India	0	0	1	0.0	0.0	1.8		11	0	0.19		4.3
Godabari[2]	Pure line	2011	FSS	0	0	1	0.0	0.0	1.8		11	0	0.19		4.1
Gorakhnath 509[1§]	Hybrid	2011	Nepal	0	0	2	0.0	0.0	3.5		11	0	0.39	123	4.5
Hardinath-1	Pure line	2004	Nepal	1	2	1	1.5	3.0	1.8	2	24	0.06	0.42	120	4
Hema[2]	Pure line	1974	India	0	0	2	0.0	0.0	3.5		48	0	1.68		4.6
Hybrid	Hybrid			0	3	0	0.0	4.5	0.0			0	0		
Jira masino	Landrace	§	§	0	0	1	0.0	0.0	1.8			0	0		
Kaberi sona[2]	Unknown	§	India	0	0	1	0.0	0.0	1.8			0	0		
Kanchhi Masuli[3]	Pure line	1992	Nepal	1	1	0	1.5	1.5	0.0	14		0.21	0.00		
Katarni[2,4]	Pure line	2008	FSS	0	0	4	0.0	0.0	7.0		14	0	0.98		4.1
Makawanpur 1	Pure line	1987	Nepal	3	0	0	4.5		0.0			0	0		
Malaysia[2,5]	Pure line	2001	FSS	1	0	0	1.5		0.0			0	0		
Masuli	Pure line	1973	Nepal	16	22	0	24.2	32.8	0.0	33		10.84	0.00	145–150	
Moti (CR 260−136 - 321 IET 9170)[2]	Pure line	1988	India	0	0	1	0.0	0.0	1.8		34	0	0.60		4.8
Mukawala 23	Pure line	2019	Nepal	0	0	1	0.0	0.0	1.8		3	0	0.05		
Panganga[2]	Unknown			0	0	1	0.0	0.0	1.8			0	0		
Radha 4	Pure line	1994	Nepal	4	2	0	6.1	3.0	0.0	12		0.36	0		
Radha-11	Pure line	1996	Nepal	3	2	0	4.5	3.0	0.0	10		0.30	0		

(Continued)

TABLE 1 (Continued)

Variety	Type of variety	Information on release or registration		Frequency of occurrence			Percentage of occurrence			Age of variety		Weighted age of varieties		Duration (days)*	Yield t/ha**
		Year	Country	2005	2006	2022	2005	2006	2022	2006	2022	2006	2022		
Ram	Pure line	2006	Nepal	9	8	11	13.6	11.9	19.3	1	16	0.12	3.09	130–137	4
Sabitri	Pure line	1979	Nepal	19	19	11	28.8	28.4	19.3	27	43	7.66	8.30	145	3.6
Sawa Masuli sub-1[6]	Pure line	2011	Nepal	0	0	9	0.0	0.0	15.8		11	0	1.74	145–150	4.9
Sawa Masuli[7]	Pure line	2019	Nepal	0	3	0	0.0	4.5	0.0			0	0		
Swarna sub-1[6]	Pure line	2011	Nepal	0	0	2	0.0	0.0	3.5		11	0	0.39	155–160	5.1
Swarna[2]	Pure line	1982	India	2	3	0	3.0	4.5	0.0	24		1.07	0		
US-305[1]	Hybrid	2019	Nepal	0	0	1	0.0	0.0	1.8		12	0	0.21	132	5.6
Total[€]				66	67	57	100	100	100						
Weighted age*												20.6	19.5		
Average grain yield															4.6
Sem															0.17

[€]The total frequency in the table for any year does not add up to 72. This is because the study recorded 6, 5, and 15 survey points without a rice crop, respectively, in 2005, 2006, and 2022. Such farms either got replaced for agricultural activities other than rice or got converted into real estate and settlements.

[1]Hybrid rice varieties are registered in Nepal. [§]Gorakhnath 509 was de-notified in Nepal but is still grown by farmers.

[2]Rice varieties from India are neither registered nor released in Nepal.

[3]A rice variety was evaluated in multi-environment trials and on farm trials during the 1990s and proposed for release in 1992, but was declined by the variety releasing committee of Nepal. Spread from farmers' seed systems.

[4]Katarni was first reported in Nepal by Witcombe et al. (2009), and it spread through farmers' seed systems.

[5]Malasia was first documented in Chitwan and Nawalparasi by Devkota et al. (2005), and it spread through farmers' seed systems.

[6]Stress-tolerant rice varieties (STRVs).

[7]Registered in Nepal 30 years after its release in India.

[§]Means not applicable, FSS, spread through farmers' seed systems.

*The age of rice varieties and crop duration were obtained from the SQCC (2022).

**The grain yield of rice varieties was collected from the 2022 GPS transect study.

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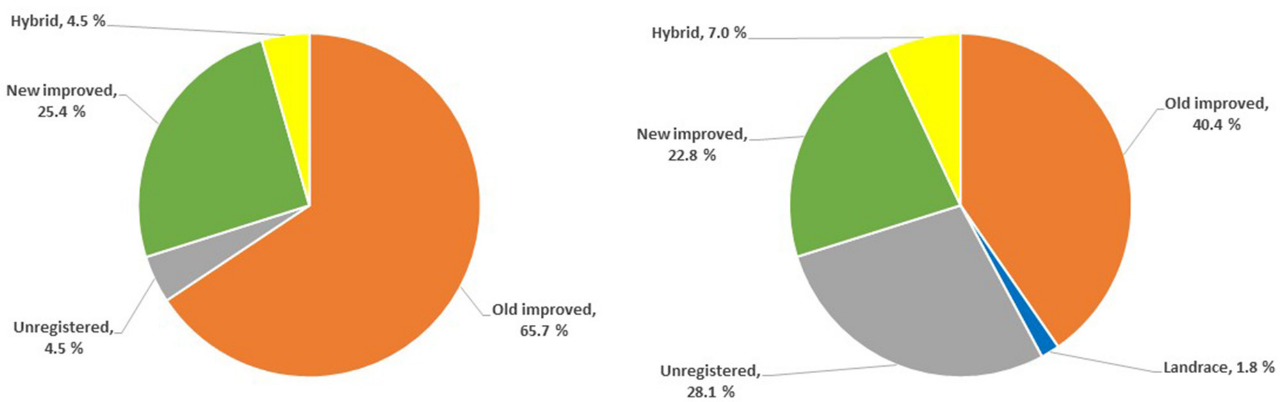

FIGURE 4
Change in rice varietal frequency (%) from 2006 **(left)** to 2022 **(right)** in eight transects with a total of 72 sampling points in Chitwan district.

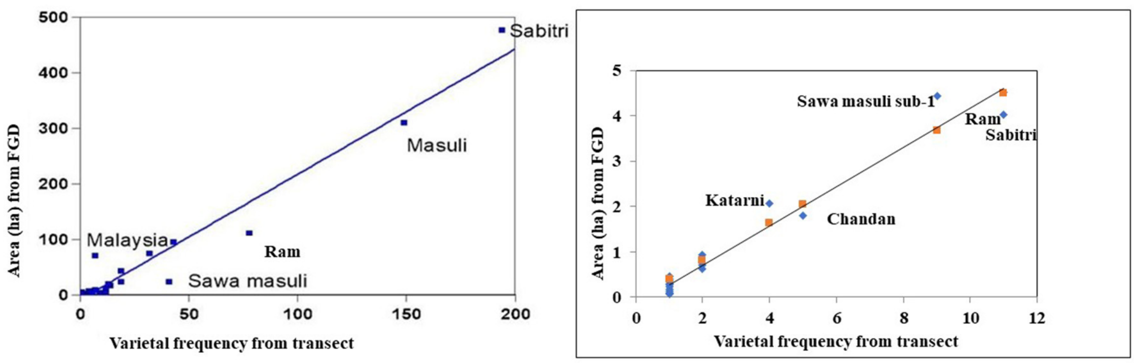

FIGURE 5
Comparison of the varietal frequency count in the transect and the estimates of the area from focus group discussion (FGD) from 14 transects in 2006 **(left)** and from eight transect in 2022 **(right)** that were common both in FGD and transect in Chitwan district, Nepal. The best fit between the two variables using linear regression is shown.

3.5. Changing land use patterns

Studies conducted in 2005 and 2006 (considering 72 GPS coordinates and sampling points) recorded rice cultivation in 86% of them, but 16 years later, it had decreased to 79%. The further shrinkage of 7% premium rice land was the conversion of 4.2% of the land to non-rice agricultural commodities, while 2.7% was converted into non-agricultural uses, such as real estate and settlements. The largest change in growing other agricultural commodities was because rice was replaced with vegetables, forage crops such as maize during the rainy season, poultry farms, cattle farms, and fishponds. Planting bananas on rice lands was also a new practice (data for individual commodities are not shown). This change depended on factors such as land type, proximity to the road head, and markets (Figure 6).

The conversion of rice fields was higher in the villages close to the *Mahendra Rajmarg* highway (largely well-drained fields). Up to 20% of rice lands in some villages were converted into non-agricultural use; the lowest conversion (5%) was reported in Phulbari, which is nearly 10 km away from the road head at Bharatpur, while in Birendranagar, Rapti Municipality, which adjoins the highway, 20% of the rice lands were converted (Figures 1, 6).

4. Discussion

4.1. Methods of evaluating varietal adoption, varietal dynamics, and change in land use patterns

The main objective of evaluating the adoption and impact of agricultural technologies is to measure their degree of success and provide information about the effectiveness of the research investment. Data from impact studies can be used to help design subsequent research better targeted to deliver multidimensional impacts, e.g., on productivity, on-farm income, poverty, and inequality. More accurate surveying enables researchers to carry out analyses that provide better evidence-based advice to policymakers (Gibson and McKenzie, 2007). Using a GPS-facilitated survey with randomly selected locations had the great advantage of providing an unbiased sampling frame based on

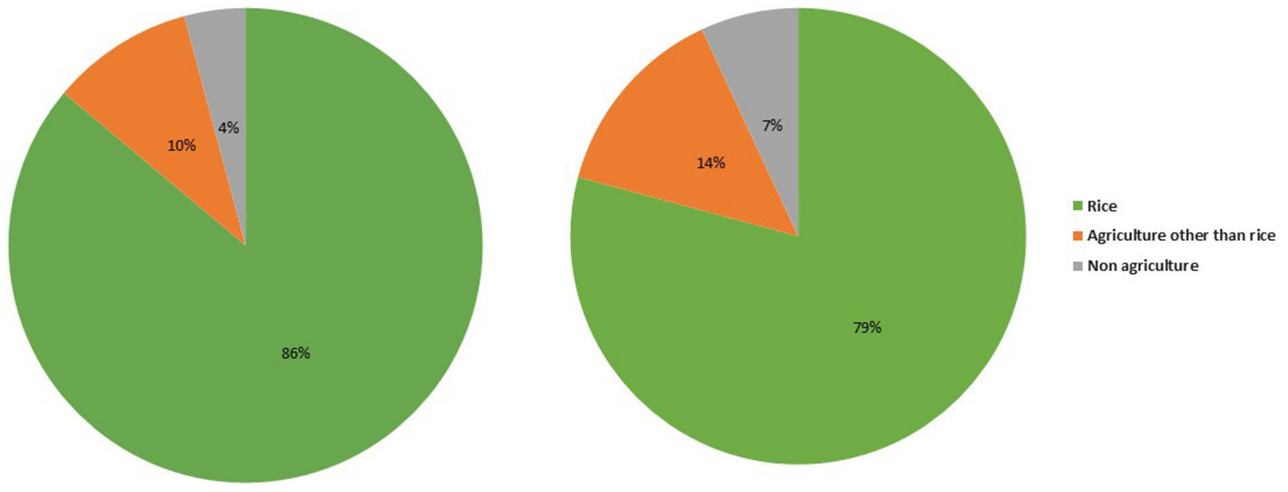

FIGURE 6
Land use change in Chitwan from 2005 to 2006 **(left)** and 2022 **(right)** across the eight transects and 72 sampling points in the Chitwan study area.

the agricultural landscape rather than on households. There is no equivalent and cost-effective way of reducing bias in samples that involve interviews with households and stakeholders. Another important advantage is that the sampling frame can be used for subsequent unbiased monitoring of changes over time, which is impracticable using households because their compositions and even their positions vary over time.

The unbiased sample was made using random numbers to identify the latitude and longitude of the sampling points. When the original study was made, there was no GPS system on mobile phones. This would now be the method of choice, and it is convenient to use the application "What3words" to handle the coordinates. This application identifies every three by three-meter square (9 m^2 area) on the surface of the earth by a unique combination of three words. The application can be used to navigate to a sampling point, and the three-letter word can then be used to identify the location of the data collected (varietal name, land type, etc.). For example, a sampling point on the Ratna Nagar transect is at 27°34′50′'N 84°15′54′'E, and this is a nine-meter square "bias.upwardly.crouched" in what3words (note that it is easier to enter the decimal equivalent of latitude and longitude into the application, in this case 27.58055N and 84.26500E). The position indicated on a mobile phone may wander slightly between adjacent named squares, but not to an extent that will change observations made at field level.

In this study, we sampled rice varieties at two different intensities; in 2006, each 1,000-m transect was sampled at 100-m intervals and at five points (the center, and 30 m east, and west, north, and south of it). In 2022, the sampling was done at 500-m intervals, and the individual points were further apart (100 m from the center instead of 30 m). The original methodology captured more rice varietal richness, particularly the rice varieties grown by farmers in small areas. Depending on the purpose of the study, the sampling intensity can vary. If the objective is to map the varietal richness and genetic diversity, more intensive sampling is appropriate, but less intensive sampling is required to evaluate the adoption of the most economically important rice varieties that are grown in the larger areas.

Focus group discussions are a more flexible and interactive tool compared with a randomly selected sampling framework, and they generate more comprehensive information. We found a high degree of agreement between the transects and the FGDs for the rice varieties grown, so the transects can be used on their own as they also provide an unbiased quantitative assessment. The FGDs do, however, capture the presence of varieties that are grown in smaller areas (Figure 5). An FGD involves the combined knowledge of participating farmers that come from different parts of a village and so effectively samples a larger area than the set points of a transect, so it was unsurprising that FGDs identified more varieties in all the three surveys. Additional data can also be collected using FGDs, such as which varieties give a higher yield or harvest value. Combining the data from transects and FGDs maximizes the benefits of both approaches.

4.2. Persistence of old rice varieties in the context of weak varietal popularization and weak seed regulatory frameworks

Rice adoption is dynamic in Nepal, as can be seen from the change in the portfolio of varieties grown over time. In the surveys done over an interval of 16 years, a total of 29 rice varieties were found in the study area, and only three were grown by farmers in both years (Sabitri, Ram, and Hardinath-1), which collectively occupied 42% of the area in 2006 and 41% in 2022. The average weighted age of the rice varieties slightly decreased from 2006 to 2022 (Table 1). The reason there was little change in the weighted average age, despite the high varietal turnover, was the persistence of these three varieties, now 16 years older.

These findings on the age of varieties agree with earlier studies. Gauchan and Pandey (2012) and Wang et al. (2012) reported that the average age of rice varieties was 24 years based on household surveys in Bangladesh, Eastern India, and Nepal and 20 years based on the expert elicitation (EE) method. Rice varietal age has been consistently above 20 years for the last decade in these countries. In Nepal, the average age of rice varieties in 2011 in 16 Terai districts was around 23 years (Witcombe et al., 2016a).

The five most widely grown varieties in the western, central, and eastern districts occupied about 70% of the area (Witcombe et al., 2016a) somewhat lower than the 82% in the 2006 survey and 78% in the 2022 survey. As in the surveys reported here, they also found that the weighted average was always higher than the average age no matter what region or year is considered.

Old and obsolete varieties, some released in the 1970s, are still grown by farmers in Nepal. This is a common phenomenon in developing countries, particularly in subsistence economies where a few old and popular varieties cover most of the rice areas (Gauchan and Pandey, 2012; Joshi et al., 2012; Witcombe et al., 2016a,b). Moreover, several of the rice varieties documented in the study were not recommended by the Seed Quality Control Center, the Seed Regulatory body of Nepal, but their seeds were sold by Agrovets (private companies trading agricultural inputs and veterinary medicines). Rice seeds of nearly 50-year-old obsolete varieties such as Hema and Moti were sold by Agrovet labeled as "new" varieties (Table 1).

Slow turnover of crop varieties is a real obstacle to delivering new genetic gains to farmers' fields and slows potential increases in rice production that will enhance food security. Since 2006, nearly three dozen rice varieties have been released in Nepal, but their uptake and adoption have been slow. Although simple and cost-effective methods for varietal evaluation and scaling up have been developed (Joshi and Witcombe, 2002; Joshi et al., 2012) such approaches have not been institutionalized. The Department of Agriculture (DoA) and the Nepal Agriculture Research Council (NARC) used to conduct country-wide Farmers' Field Trials (FFTs) and Minikits (seed kits) of pipeline or recently released crop varieties, but these activities are no longer prioritized by these organizations. However, the slow uptake of new varieties is not only determined by the promotion and availability of seed for new varieties. There is also the extent of demand for the grain of a variety to consider. In the FGDs, farmers reported that one reason they continued to grow Sabitri and Ram was the existence of an established market for their grain. Rice millers, major purchasers of grain, have an incentive to continue with older varieties as an established market reduces the risk of having unsold grain. Replacing them with newer varieties increases risk, e.g., they may be less accepted by consumers. Moreover, economies of scale are reduced because it is almost inevitable that the grain of newer varieties will be in shorter supply.

4.3. Changing land use patterns

Migration and urbanization have complex implications for land use change in Nepal. Many researchers acknowledge that conversion of fertile lands into real estate will result in the loss of arable lands with reduced food production, leaving communities vulnerable to food shortages and price fluctuations and disrupting food security. Rimal et al. (2018), in a study covering 27 years, reported significant loss of cultivated land due to urbanization in the Nepal Terai. The urban cover of 221 km^2 in 1989 increased to 930 km^2 by 2016 (a 320% increase), and of the new urban cover added since 1989, 93% was formerly cultivated land. Paudel et al. (2014) reported that the migration resulted in the abandonment of productive agricultural lands in the mid-hills of Nepal.

Rampant urbanization and land fragmentation triggered by real estate developers between 1989 and 2016 are two of the major constraints to attaining food security in the country (Shrestha, 2017; Timsina et al., 2019; Dahal, 2023). According to Shrestha (2017), more than 70% of the rice lands in Lekhnath region of Pokhara Metropolitan have already been converted into settlements, and the remaining 30% are also being bought up by real estate developers, says Kamal Bahadur Thapa, the Ward Committee chairman of the metropolitan, who blames the local government for an unplanned growth of urbanization. The study also reported that high-quality heritage varieties such as Jethobudho, Pokhreli Masino, Jhinuwa, Ramani, and such other heritage rice are on the verge of extinction due to the conversion of irrigated lands in Pokhara and Lekhnath, which are the habitats for these rice landraces. In the last decade, 99% of those who migrated to the Middle East or Malaysia shifted to towns, and families of migrant workers invested in real estate. It is reported from eastern Terai that in the last 15 years, one out of every three Nepalese has left their villages to settle in urban and peri-urban areas, resulting in a heightened demand for housing and land in urban areas, subsequently leading to an increase in prices. The price of urban land in Kathmandu city was US$ 22,000 m^2, ranking among the top 10 most expensive real estates in the world (Ghimire, 2022; Dahal, 2023). But this price trend for real estate extends throughout the country, and the article also reported that the growth rate of property value in Nepal is 27.7%, which means that real estate values are doubling every 3.5 years. Loss of farmlands over the years has been reflected in the sharp hike in food imports that increased from US$157 million in 1995/96 to over USD$1.378 billion in 205/16 and over USD$3 billion during 2022 (Bhavana and Race, 2019; DoC, 2022). A lack of decentralized development in the country has forced families to settle in lands known for their high agricultural productivity, in the valleys or in the plain areas of the Terai, where better school and health facilities are located. Rimal et al. (2018) revealed that land use change in the Terai is caused by significant inter-regional migration coupled with poor urban planning and lax policies for controlling the fragmentation of peri-urban cultivated lands. They suggested that urban-growth management may reduce agricultural land losses in Nepal.

5. Conclusion and recommendation

Varietal adoption and dynamics can be evaluated using GPS-determined transects that provide an accurate and unbiased sampling frame. It can be used to evaluate, over time, the uptake and adoption of agricultural technologies as well as changes in natural resources. It is now very easy for anyone to use this technique by using a mobile phone to geolocate the points.

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GPS-based studies can have strategic importance by creating a long-term data base that reliably documents changes in the patterns of adoption of agricultural technologies and natural resources. One can exactly repeat the survey at any time by using the geographic coordinates of the initial study.

The study reaffirmed the dominance of old-improved rice varieties, and this has serious implications for delivering new genetic gains to farmers' fields and for achieving food and nutrition security in Nepal. Of late, varietal deployment and popularization by public sector agriculture research and extension are not very effective, as seen by the slow and limited adoption of newly released rice varieties in a highly accessible area such as Chitwan. An additional factor is the time needed to establish a market for the grain of new varieties because grain purchasers are motivated to buy varieties that have an already-established demand from consumers.

Due to a lack of planned urbanization and appropriate policies in place, widespread conversion of fertile lands into real estate in the Terai and valleys and underutilization and abandonment of agricultural lands in the hilly areas pose the biggest threat to food and nutrition security in Nepal, which is likely to be exacerbated if the current trends related to land use and land cover changes are not addressed with the right policies and other appropriate instruments.

We recognize two limitations to the study. (i) The GPS devices used during 2005, 2006, and 2022 were not the same, and this may have affected the precision of the study to some extent. (ii) The population in any spatial area is likely to be unevenly distributed; therefore, it may not fully represent the entire population.

Future research on the topic can be conducted with a multi-stage sampling approach where the number of samples and GPS coordinates are predetermined based on the population size in each location and spatial points are randomly selected.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

JW designed the research, quality control, and write up and analysis. KJ led the analysis and write up of the article and overseeing field surveys as well as checking data quality. KR and GJ conducted field research during 2005 and 2006 and data compilation as well as contributing to write up. NK and SU conducted field research in 2022, data compilation, analysis, and contributed to write up. KD contributed in field research, data analysis, and write up. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

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Impacts of the joint adoption of improved varieties and chemical fertilizers on rice productivity in Bolivia: implications for Global Food Systems

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Rice research and technology development in Latin America has increased yields and offered the opportunity for several countries to contribute to global food security by becoming net exporters of this cereal. In spite of the broad availability of rice technologies in the region, rice yields remain substantially low in countries like Bolivia. This study examines how Bolivian rice growers make simultaneous decisions about adopting improved varieties and chemical fertilizers and how this joint decision influences the productivity of this crop. By exploiting a nationally representative survey of rice producers, we use a multinomial logit model and an optimal instrumental variable approach to study both the correlates of technology adoption and the impacts of this adoption on rice yields. Our findings suggest that partial adoption of rice varieties or fertilizers does not affect yields, but the joint adoption of these technologies can almost double rice productivity. Promoting packages of agricultural technologies—instead of single technologies within efforts to make these technologies available for small farmers—would exploit the complementarities of different technologies and boost rice yields in Bolivia. The implications would not only be to achieve the desired self-sufficiency in rice production but also to follow similar pathways of other countries in the region that have become net exporters of rice and are contributing to Global Food Systems.

KEYWORDS

***Oryza sativa L.*, technology adoption, improved crop varieties, impact assessment, multivalued endogenous treatment effect**

1. Introduction

Productivity growth of rice (*Oryza sativa L.*) in recent decades in Latin America has increased the per capita consumption of this cereal and specifically improved the diets of the poor in the region (Zorrilla et al., 2012; FONTAGRO, 2019). As such, several countries have become net rice exporters, showing major potential for the region to contribute to Global Food Systems. However, this yield enhancement in rice production, showing average rice yields between 8 and 10 t/ha, has not reached all rice-producing countries. In spite of the availability of improved varieties and other agronomic technologies in the region, countries like Bolivia keep an average rice yield of ~3 t/ha (FAOSTAT, 2023).

Although the technological progress of rice production made in Latin America has been well-documented (Calvert et al., 2006; Zorrilla et al., 2012; Martínez et al., 2014), evidence on the uptake of improved rice technologies and their impact on productivity and development outcomes remains limited. Few studies have documented the level and factors that may explain the adoption of improved varieties, fertilizers, and other inputs in rice production in Latin America (Scobie and Posada, 1978; Strauss et al., 1991; White et al., 2005; Morello et al., 2018; Marín et al., 2021; Martinez et al., 2021). However, understanding how adopting improved rice technologies could translate into productivity and welfare impacts in Latin America remains absent.

In Bolivia, rice production represents one of the main sources of income and food security for rural households (Ortiz and Soliz, 2007; MDRyT, 2012). However, the use of improved rice technologies among small and medium-scale farmers remains constrained (Martinez et al., 2021). This low adoption of rice technologies has restrained the Bolivian rice sector from improving yields, facilitating greater participation in local and regional markets (Lopera et al., 2023), and reducing price volatility for producers (Bauguil, 2003) and consumers in urban areas (Perez et al., 2011). With a large share of agricultural land under rice, an improvement of rice productivity to the average rice yields in Latin America could meet the domestic demand and transform Bolivia into a net exporter of this cereal. Exploring the relationship between the uptake of rice technologies and rice productivity in the Bolivian context may help policymakers in designing better strategies to achieve a significant productivity jump, as experienced by similar countries in Latin America.

The agricultural economics literature has extensively documented the impacts of agricultural technology adoption on other crops (Feder and Umali, 1993; De Janvry and Sadoulet, 2006; Doss, 2006) or for rice in other regions (Yamano et al., 2016; Mishra et al., 2022). Wang et al. (2020) reported positive and significant impacts of stress-tolerant rice varieties on yields and income in Yunan, China. Likewise, while Yamano et al. (2018) highlighted the difficulties in adopting natural resource management rice technologies, Mishra et al. (2022) reported that rice technologies on direct seeding, rodent control, and iron toxicity removal significantly affect economic wellbeing. Finally, Mills et al. (2022) found that salinity-tolerant rice varieties increased yields on fields that are not protected by salinity barriers in the Mekong Delta. Still, lower market prices limit the overall economic benefits of these varieties compared to other varieties.

One limitation of the available evidence on the impacts of rice technologies has been the focus of the analysis on the adoption of single technologies. However, a growing body in the broader agricultural technology literature is undertaking the analysis from the perspective of "technological packages." As such, these studies explore the effects of packages of technologies (e.g., improved varieties, along with sustainable agriculture practices) on several outcomes, incorporating the complementarities that joint adoption of technologies can offer. Teklewold et al. (2013) used a multinomial endogenous switching regression, finding that the combined adoption of improved maize varieties and minimum tillage resulted in higher income among farmers in Malawi. However, it also increased family labor demand, especially for women. Meanwhile, using a similar approach, Martey et al. (2023) found that the joint use of Striga-resistant maize and fertilizers had significant positive effects on yields and food consumption. Likewise, using a similar approach, Kassie et al. (2015) found evidence of improved food security and reduced downside risk when Malawian farmers simultaneously adopted maize varieties and chemical inputs. Despite the use of technological packages in the African context, studies that evaluate these packages are not common for rice technologies and are non-existent in Latin America.

This article aims to fill in the gaps as well as provide evidence on whether the joint adoption of modern improved rice varieties (MIV) and chemical fertilizers could lead to a significant rice yield increase in Bolivia. Given that the increase in rice acreage is not feasible in Bolivia, increasing rice yields eventually will support the aspiration of the country to achieve rice production self-sufficiency and become a net exporter of this cereal. We take advantage of a comprehensive household and plot survey on a nationally representative sample of Bolivian rice producers and use an instrumental variable approach to control for potential selection bias in the estimation procedure.

We found that the adoption of rice technologies is positively correlated with farm size, being a member of a farmer organization and having access to agricultural credit. Conversely, we found evidence that the adoption of these technologies is discouraged by having other sources of farm income. On the other hand, once we accounted for the potential endogeneity of the decision to adopt rice technologies, we found that individual use of either improved rice varieties or chemical fertilizers does not influence rice yields. However, when both technologies are jointly adopted, rice yields are almost doubled (+1.67 t/ha).

2. Rice production and access to improved technologies in Bolivia

Although soybeans and other industrial crops in Bolivia have become the main source of country revenue and forex, rice and other cereals remain the main source of income and food security for small and medium farmers (Ortiz and Soliz, 2007). There are over 180,000 ha of rice in Bolivia (90% cultivated under rainfed conditions), managed by approximately 45,000 farmers (Lopera et al., 2023). Approximately 95% of rice production is concentrated in the Santa Cruz, Beni, and Cochabamba regions.

Between the 1960s and 1980s, average rice yields in Bolivia (2.1 t/ha) were not different from the average yields in Latin America and were slightly higher than that in Brazil, the leading producer and consumer of rice in the region (Table 1). By the early 1980s, the strengthening of several rice improvement programs in the region made various improved varieties available that adapted to different local conditions. Likewise, other countries started promoting improved agronomy in rice production (Zorrilla et al., 2012). It did not take long to observe different countries in the region progressively increasing rice productivity, bringing the current average yield in Latin America to 4.49 t/ha (Table 1). This productivity transformation has made countries like Brazil, Paraguay, Uruguay, and Argentina become net rice exporters

TABLE 1 Average rice yields (t/ha) evolution in a selected group of Latin-American countries.

Period	Latin-America	Bolivia	Brazil	Argentina	Colombia	Nicaragua	Paraguay	Peru	Uruguay
1961–1980	1.58	1.57	1.50	3.57	3.20	2.68	2.17	4.13	3.67
1981–1990	2.00	1.67	1.76	3.87	4.48	3.33	2.29	4.80	4.90
1991–2000	2.63	1.96	2.57	4.87	4.35	3.37	3.86	5.75	5.60
2001–2010	3.39	2.30	3.66	6.09	4.70	3.68	3.85	6.88	6.95
2011–2021	4.49	2.86	5.75	6.72	5.11	5.72	6.29	7.79	8.32

and contributors to Global Food Systems (FAOSTAT, 2023). Conversely, this productivity boom has not reached Bolivia, with its average rice yield remaining at only 2.86 t/ha. This low productivity has made Bolivia heavily dependent on rice imports, which reached 72,000 tons in 2014 (FAOSTAT, 2023).

Rice is not native to Latin America, and Bolivia heavily depends on improved varieties or advanced breeding lines introduced from neighboring countries (Taboada et al., 2000). Initially, the Bolivian Rice Improvement Program introduced materials from Brazil, the USA, and Southeast Asia. However, in 1997 with the establishment of the Centro de Investigación Agricola Tropical (CIAT-Santa Cruz) and its collaboration with the Latin-American Fund for Irrigated Rice (FLAR), the breeding program started a phase of population improvement through recurrent selection (Taboada et al., 2005). This brought a variety of modern improved varieties (MIV) to Bolivian rice farmers. The new varieties' traits included high yielding, higher micronutrient content (Viruez and Taboada, 2013), and water-use efficiency (Grenier et al., 2010). Between 2004 and 2014, 12 MIVs were released in Bolivia and are the focus of this article. Some of the MIVs have been planted consistently in between 45 and 60% of the rice acreage since 2013 (Martinez et al., 2021) without significant changes over time (Taboada and Viruez, personal communication, March 2023).

The other 40–55% of the rice areas have also been under improved rice varieties, despite being old varieties and not bred specifically to address the production conditions in Bolivia. However, the use of these old improved varieties may be explained by the limited capacity of the country to produce certified seeds (Martinez et al., 2021). Until the late 1990s, there were no consistent efforts to produce large quantities of certified rice seed (Ortiz and Soliz, 2007). However, between 2000 and 2005, a center for certified seed production was established in San Juan de Yapacani Cooperative, with financial support from the Japanese Cooperation (OPMAC Consulting, 2009). This cooperative, integrated by Japanese descendants cultivating rice since 1951 and engaged with the technical backing from the CIAT-Bolivia, produced enough certified seed to cover 23% of the total rice area in the country (Vargas, 2014). Unfortunately, the end of the initiative discouraged many of the cooperative seed producers to continue producing certified rice seed and, therefore, the supply was reduced (OPMAC Consulting, 2009).

Although San Juan de Yapacani was also used to disseminate recommendations for better agronomic management of rice production, there was no equivalent program to the certified seed that could make other agricultural inputs broadly available, including chemical fertilizers (Viruez and Taboada, 2013). The use of chemical fertilizers has been traditionally low in Bolivian agriculture, with an average of 5.3 kg/ha compared with the 107.4 kg/ha applied on average in Latin America (Vargas, 2014). In the rice sector, only farmers with access to irrigation have been able to use the recommended quantity of chemical fertilizers, but this group only represents 10% of the total area under rice production (Ortiz and Soliz, 2007). In general, the low use of fertilizers in Bolivia is associated with the high cost and the lack of domestic production in Bolivia (Killeen et al., 2008).

In the 1980s and 1990s, there were some attempts to promote kits or packages of agricultural inputs in the country but, in general, farmers were splitting the kits and adopting the agricultural inputs independently (Godoy et al., 1998). Only more recently, and with the explicit policy of the government to achieve greater competitiveness in agriculture to improve access to domestic and international markets, the promotion of packages of rice technologies has started to be implemented (Killeen et al., 2008; World Bank, 2018). However, the recommended usage of chemical fertilizers in these packages has not been based on farm-level soil testing, which is required for the optimal use of this input (Murphy et al., 2020). Recently, some agricultural development projects led by the National Institute for Agricultural and Forestry Innovation (INIAF) and the World Bank have promoted the joint use of certified seeds and agronomic practices, reporting yield increases of up to 100% (World Bank, 2018). Nevertheless, this yield increase estimation was not done using a counterfactual framework and focused on selected farmer groups, not representing the potential effect at the national level. This fact may not allow drawing definite recommendations for a broader scaling-up of these initiatives.

3. Materials and methods

3.1. Theoretical framework and econometric approach

Over the years, agricultural land and labor markets in Bolivia—and Latin America, more broadly—have presented pronounced failures that have restricted different production factors from being allocated efficiently (Bauguil, 2003; World Bank, 2018). To model farmers' decision to adopt improved rice technologies, we follow an agricultural household model framework that allows farmers' production decisions to be non-separable from meeting household consumption objectives (Bardhan and Udry, 1999; De Janvry and Sadoulet, 2006). In our case, factors beyond rice and inputs prices, namely, households' consumption preferences and attributes, play a role in determining choices on technology adoption. Ultimately, a representative household makes a decision on the technologies used for rice production to maximize its expected utility.

Let there be J possible (mutually exclusive) packages of technologies available to produce rice, such that the indirect utility derived by the implementation can be defined as follows:

$$V_j = \mathrm{x}\theta_j + e_j, \quad for\ j = 1, ..., J \tag{1}$$

where x is a $1 \times K$ vector of attributes of the household, θ_j is a $K \times 1$ vector of unknown parameters, and e_j is an error independently and identically Gumbell (0,1) distributed. While V_j is unobservable, we observe whether the technological package j is adopted in the farm. Under a maximization process, the household chooses package g if and only if $V_g \geq V_j$, for all $g \neq j$, for $g, j \in \{1, ...J\}$. Let $d_j \in \{0, 1\}$ be defined as $d_j = 1\left[adopts\ package\ j\right]$, which implies $\sum_{j=1}^{J} d_j = 1$ from mutual exclusion. Under this setting, the probability of adopting a technological package j follows from a multinomial logit (MNL) model (McFadden, 1973) such that:

$$\begin{aligned} \Pr\left(\text{Adopting package j} \mid \mathrm{x}\right) &= \Pr\left(\mathrm{d_j} = 1 \mid \mathrm{x}\right) \\ &= \frac{\exp\left(\mathrm{x}\theta_{\mathrm{j}}\right)}{\sum_{\mathrm{t}=1}^{\mathrm{J}} \exp\left(\mathrm{x}\theta_{\mathrm{t}}\right)}, \end{aligned} \tag{2}$$

and the partial effects follow:

$$\begin{aligned} &\frac{\partial \Pr\left(d_j = 1 \mid \mathrm{x}\right)}{\partial x_k} = Pr\left(d_j = 1 \mid \mathrm{x}\right) \\ &\times \left\{\theta_{jk} - \frac{\sum_{t=1}^{J} \theta_{tk} \exp\left(\mathrm{x}\theta_t\right)}{\sum_{t=1}^{J} \exp\left(\mathrm{x}\theta_t\right)}\right\}; \end{aligned} \tag{3}$$

hence, the sign of coefficient estimates, $\hat{\theta}_{jk}$, does not necessarily provide a direction of the partial effects (Cameron and Trivedi, 2005; Wooldridge, 2010).

In our case, we focus on the two most spread technologies available for rice production in the Bolivian context, namely, modern improved varieties and chemical fertilizers (Rodriguez, 2009), which have long been the main production-enhancement strategies promoted by the Bolivian agricultural authorities (MDRyT, 2012). Hence, there are four feasible mutually exclusive technological packages ($J = 4$) that the rice-farming households can choose from, namely, no adoption of either technology, only MIV, only chemical fertilizers, or joint adoption of both MIV and fertilizers.

3.1.1. Impacts of technology adoption: average treatment effects

Our main target is measuring the impacts associated with the adoption of MIV and chemical fertilizers. Most previous studies on the impacts of joint technology adoption in agriculture have followed a multinomial endogenous switching regression approach (e.g., Teklewold et al., 2013; Kassie et al., 2015; Khonje et al., 2018; Shafiwu et al., 2022) focusing on estimating the average treatment effects on the treated (ATT). However, we are interested in measuring the potential impacts at the scale of the adoption of these technologies. We, therefore, should also consider those farmers who would not be "treated" in the *status quo*. Our analysis then focuses on estimating the average treatment effects (ATE) of technology adoption on rice production via optimal instrumental variable methods and exploiting an MNL model.

Following Kekec (2021), we assume that a household chooses a single technological package $j \in \{1, 2, 3, 4\}$ of agricultural inputs, let the outcome of yields under technology package j be given as follows:

$$y_j = \alpha_j + \mathrm{m}\delta_j + u_j, \tag{4}$$

where m is another $1 \times M$ vector of household attributes, δ_j is another $M \times 1$ vector of unknown parameters, and u_j is a random error. Now, let $j = 1$ be the base group for comparison of technology packages, namely, no implementation of either improved rice varieties or fertilization. Hence, the average treatment effect from using a package j to no use of enhancing practices is given as follows:

$$\begin{aligned} ATE_{j,1} &= E\left(y_j - y_1\right) \\ &= \left(\alpha_j - \alpha_1\right) + E\left(\mathrm{m}\right)\left(\delta_j - \delta_1\right). \end{aligned} \tag{5}$$

Hence, a proper estimator of the *ATE* would plug in consistent estimators derived from a sample of n individuals, namely, $\hat{\alpha}_j$ and $\hat{\delta}_j$, for $j = 1, ..., J$, and $\bar{\mathrm{m}} = \frac{1}{n}\sum_{i=1}^{n} \mathrm{m}_i$. That is, we can simply set up an estimator of the form:

$$A\hat{T}E_{j,1} = \left(\hat{\alpha}_j - \hat{\alpha}_1\right) + \left(\bar{\mathrm{m}}\right)\left(\hat{\delta}_j - \hat{\delta}_1\right), \tag{6}$$

which can be further reduced to $A\hat{T}E_{j,1} = \left(\hat{\alpha}_j - \hat{\alpha}_1\right)$ whenever $\bar{\mathrm{m}} = \mathbf{0}$ or no heterogeneity is added to the yield outcome.

As noted in Kekec (2021), we only observe the outcome under technology j (Equation 4) for those who effectively adopted technology package j within the sample. That is, the empirically observed yield outcome follows:

$$\begin{aligned} y &= d_1 y_1 + d_2 y_2 + d_3 y_3 + d_4 y_4 \\ &= \sum_{j=1}^{4} d_j \alpha_j + \sum_{j=1}^{4} d_j \mathrm{m}\delta_j + \zeta \end{aligned} \tag{7}$$

where $\zeta = d_1 u_1 + ... + d_4 u_4$. Since every d_j is in ζ, estimating (7) by ordinary least squares (OLS) will provide inconsistent estimators of α_j and δ_j, for all j. Standard instrumental variable methods would fail to account for the endogeneity in all d_j since they are also in ζ, hence failing the exclusion restriction. Nevertheless, Kekec (2021) noted that we can obtain consistent estimators by following an alternative approach in two steps[1]:

1. From a multinomial logit model of technology adoption, retrieve the predicted probabilities: $\hat{\Lambda}_{ij} = \exp\left(\mathrm{x}_i\hat{\theta}_j\right) / \sum_{t=1}^{4} \exp\left(\mathrm{x}_i\hat{\theta}_t\right)$, and then
2. Estimate Equation (7) by two-stage least squares (TSLS) using instruments $\left(\hat{\Lambda}_{ij}, \hat{\Lambda}_{ij}\mathrm{m}_i\right)$ for $\left(d_{ij}, d_{ij}\mathrm{m}_i\right)$, hence achieving consistent estimates of α_j and δ_j, for $j = 1, 2, 3, 4$.

This approach differs from traditional instrumental variables in that it uses optimal instruments and achieves asymptotic variance minimization. In addition, an important feature of this approach

1 If all elements of m are in x, identification requires that $\dim(\mathrm{x}) > \dim(\mathrm{m})$.

is that such optimality and consistency hold regardless of whether the multinomial logit is the correct underlying model of technology adoption. This reveals a clear drawback of endogenous switching regression or control function methods, which entirely rely on having the correct model for achieving consistency by including proper additional variables in the regression of interest. Finally, we can retrieve our desired measure of treatment effects by plugging in the TSLS estimates into Equation (6). Furthermore, we can obtain correct standard errors by bootstrapping (Wooldridge, 2010). Our analysis focuses on a case with no additional heterogeneity in yields (i.e., we set $\delta = \mathbf{0}$), as such addition only brings precision at the cost of requiring further instruments, which, on average, increases the odds of weak instrumentation. Our main assumption for identification is to consider membership to a farmer' association, extension services, and access to credit for agricultural inputs as variables that affect yields only through their effect on the adoption of improved varieties and fertilization.

While our approach would have also been suitable for estimating the impacts of the adoption of rice technologies on rice income, limitations on the available data made it difficult to include this outcome variable in the analysis. However, as our theoretical framework assumes that technology adoption is welfare-enhancing given that farmers make choices that maximize utility, we perform a statistical analysis to compare the Poverty Probability Index (PPI) (IPA, 2017) and the Household Dietary Diversity Score (HDDS) (FAO, 2010) across the different adoption groups.

3.2. Data

We used cross-sectional information on rice farmers in Bolivia, where producing households reported information on the main production season of 2013. This dataset, initially explored by Martinez et al. (2021), is nationally representative of the adoption of modern improved rice varieties.[2] The survey also collected information about the adoption of other agricultural practices and household socioeconomic characteristics. Sampling followed a multistage strategy, where the primary sampling units (clusters) were communities with an optimal size of roughly 14 households per community. A total of 775 households were considered in the analysis.[3] Table 2 summarizes the averages of relevant variables to our modeling strategy disaggregated by the defined technological packages. Noticeably, the largest share of farmers in our sample (45.3%) did not use either modern improved varieties (MIV) or chemical fertilizers, which is our base comparison category. Meanwhile, the adoption of only MIV reached 28.9%, while adopters of only fertilizers corresponded to 8.5% of the sample. Finally, rice-farming households using MIV and chemical fertilizers represented 17.3% of the sampled households. Due to infrequent bookkeeping among Bolivian rice farmers, it was neither possible to include the fertilization rate in the analysis nor was it possible to estimate the rice income. As expected, the lowest average yield was found among non-adopters at 1.89 t/ha, although this was not too different from the average yields of farmers adopting only chemical fertilizers (1.93 t/ha). On the other hand, adopters of only MIV had an average yield of 2.19 t/ha, and adopters of the combination of MIV and fertilizers reported an average yield of 2.79 t/ha.

Of note, 40% of total crop production in our sample was devoted to rice, and the average rice acreage fell into the small/medium-scale farm definition (97.4% of the sample). The descriptive statistics in Table 2 also show that while non-adopters had the lowest average farm size (32 ha), farmers adopting both MIV and chemical fertilizers had, on average, 94 ha. Adopters of only one technology (MIV or fertilizers) were more around the mid-size farms of the sample.

There was a higher percentage of being a member of a farmer organization, having received extension services, and receiving credit for purchasing agricultural inputs among the adopters of rice technologies. The percentage of farmers receiving extension and using credit services was larger among the fertilizers-only adopters (27.3 and 21.1%, respectively) than among MIV-only adopters (21 and 13.8%); however, we observed the opposite trend among those who were part of a farmers' association (15.2% *vis-à-vis* 21.4%). Likewise, adopters of the MIV and fertilizers were located farther from San Juan the Yapacaní, the main center of diffusion of rice technologies in Bolivia. On average, adopters of MIV-only, fertilization-only, or dual-adopters were, respectively, 8, 49, and 59% closer to the diffusion center than the in-sample average. In contrast, non-adopters were ∼36% farther away than the average farmer.

We also included in the analysis off-farm income and revenues from animal and by-product sales as covariates, as these sources of income may show a transition out of agricultural production (Larochelle and Alwang, 2015). Our sample showed that dual-adopters had the highest off-farm income on average. Conversely, revenues from animal and by-product sales were reported only by between 27 and 32% of the different types of adopters of rice technologies. Finally, schooling levels were higher among single or dual adopters than among non-adopters.

While the analysis of this 10-year-old dataset may raise questions about the relevance of the results and their policy implications, the rice production, consumption, and marketing conditions remain similar to the situation described in 2013

2 The total sample used in Martinez et al. (2021) was of 802 observations, and was nationally representative, following a two-stage random procedure (First selected primary sample units (PSU) and then households in each PSU). To estimate the minimum sample required, we first estimated a simple random sample expecting to estimate up to 60% of adoption of MIV, a 95% level of confidence and a 3.5% level of precision. Then, to account for the two-stage procedure, we included a conservative intra-class correlation of 0.05 and estimated a design effect of 1.55. Thus, the simple random sample grew from 497 households randomly distributed among major rice producing areas to 770 households selected in at least 65 PSU. We ended up interviewing 845 households in 98 farm communities but had a valid sample of 802 households. The current study uses 775, which is a reduction of 27 observations. This was due to the lack of reliable yield data on these 27 observations, but the sample remains nationally representative. We have added a footnote to explain in detail the sampling procedure.

3 The full sample used in Martinez et al. (2021) consisted of 802 observations, but for this paper analysis, complete information on rice yields and main covariates was only available for 775 households due to limited bookkeeping.

TABLE 2 Descriptive statistics of the sample.

	Sample		No adoption		Improved varieties (MIV)		Fertilization		MIV + fertilization	
Share of sample	–		45.3%		28.9%		8.5%		17.3%	
Variables	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Farm size (ha)	51.60	106.8	31.68	45.0	58.11	91.4	47.81	64.1	94.74	205.0
Paddy rice yield (t/ha)	2.13	1.4	1.89	1.27	2.19	1.4	1.93	1.53	2.79	1.48
Share of rice within the farm (%)	42.84	37.7	40.21	40.8	44.69	35.9	48.20	38.6	43.98	30.8
Member of a farmer association (1 = yes) (%)	15.9		7.1		21.4		15.2		29.9	
Received extension services (1 = yes) (%)	18.5		11.1		21.0		27.3		29.1	
Received credit for purchasing agricultural inputs (1 = yes) (%)	13.0		4.8		13.8		21.2		29.1	
Distance to San Juan de Yapacaní (log scale)	4.00	1.4	4.36	1.3	3.92	1.3	3.51	0.9	3.41	1.6
Schooling of the head of the household (years)	6.08	4.3	5.25	3.8	6.73	4.4	5.58	4.2	7.43	5.0
Age of the head of the household (years)	45.95	12.5	46.65	12.9	45.73	12.8	47.06	12.3	43.92	11.1
Off-farm income in the household (1 = yes) (%)	48.1		45.9		48.7		47.0		53.7	
Income from animal sales and by-products (1 = yes) (%)	31.9		35.3		27.7		31.8		29.9	
Beni (%)	29.4		42.5		26.3		9.1		10.4	
Cochabamba (%)	10.3		8.3		17.0		9.1		5.2	
Observations	775		351		224		66		134	

Source: elaborated by the authors.

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TABLE 3 Coefficient estimates for multinomial logit (MNL) model of technology adoption.

Variables	(1) Improved varieties (MIV)	(2) Fertilization	(3) MIV + fertilization
Farm size (log scale)	0.334** (0.136)	0.420*** (0.162)	0.818*** (0.150)
Share of rice within the farm (%)	0.015*** (0.005)	0.020*** (0.006)	0.020*** (0.006)
Member of a farmer association (1 = yes)	0.734* (0.409)	0.227 (0.485)	1.015*** (0.334)
Received extension services (1 = yes)	0.169 (0.330)	0.583* (0.317)	0.363 (0.319)
Received credit for purchasing agricultural inputs (1 = yes)	0.641* (0.389)	0.908** (0.435)	1.043*** (0.375)
Distance to San Juan de Yapacaní (log scale)	−0.014 (0.098)	0.026 (0.133)	0.031 (0.142)
Schooling of the head of the household (years)	0.061** (0.028)	−0.004 (0.044)	0.042 (0.032)
Age of the head of the household (years)	0.007 (0.009)	0.007 (0.014)	−0.011 (0.011)
Off-farm income in the household (1 = yes)	−0.063 (0.200)	0.013 (0.286)	0.220 (0.239)
Income from animal sales and by-products (1 = yes)	−0.363 (0.222)	−0.403 (0.333)	−0.404* (0.244)
Constant	−2.746*** (0.846)	−3.966*** (1.202)	−4.540*** (0.971)
Observations	775	775	775
Department controls	Yes	Yes	Yes

Clustered standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.
Source: elaborated by the authors.

(Taboada and Viruez, personal communication, March 2023). Furthermore, current agricultural policies to support the increased productivity and competitiveness of Bolivian agriculture and to mitigate the effects of the COVID-19 pandemic are calling for enhancing the access to improved crop technologies that could lead to Bolivia's self-sufficiency and export orientation (MDRyT, 2017, 2021).

4. Results and discussion

For our identification strategy, we required that the instruments have sufficient explanatory power within the multinomial logit (MNL) model of technology adoption. We report the estimates of the covariates in the MNL specification and their marginal effects in Tables 3, 4, respectively. Our findings showed a positive and significant effect of receiving credit for production inputs across all possible adoption of rice technologies scenarios (Table 3). Farm size and being a member of a farmers' association also had positive effects, although among MIV-only or dual adoption. On the other hand, extension services only significantly affected the adoption of chemical fertilizers. We did not find a significant effect on the adoption of any rice technology due to the distance to the main rice technological center in Bolivia, which differs from an earlier analysis (Martinez et al., 2021). However, both results are not directly comparable. While Martinez et al. (2021) explored the joint determinants of adoption unconditional to other technologies, our estimation specifically conditions whether other inputs are accounted for in the production system.

Focusing on marginal effects estimation, we found that most covariates clearly reduced the odds of being a non-adopter (Table 4). On the other hand, we found that the magnitude of the increase in the probability of adopting a specific technological package varied across the three adoption scenarios. A 1% increase in farm size increased the odds of becoming a full adopter by 0.07% points, while it decreased the odds of being a non-adopter by 0.09% points. In addition, being a member of a farmers' association reduced the odds of opting out of technology by 14.1% points. In comparison, it increased the odds of becoming a dual adopter by 7.9% points. That being said, receiving credit for rice production was correlated with an increase of 7.4% points in the likelihood of using both technologies. On average, an additional year of schooling increased the odds of adopting MIV by 1% point, while at the same time, it reduced the probability of being a non-adopter. Having animal sales as a source of income seemed to discourage technology adoption, making farmers 7.4% points less likely to use either chemical fertilizers or MIV, on average. Finally, we found no significant marginal effects of accessing extension services, the distance to the main rice technological center, or off-farm income on the adoption decisions.

Table 5 reports the estimated average treatment effects (ATE) of adopting different rice technologies on rice paddy yields, comparing OLS and TSLS estimates. Columns 1 and 3 compare the results in levels, whereas columns 2 and 4 take the comparison to logarithmic scales (percentage increases). Under the assumption of strict exogeneity of the decision to adopt rice technologies, the adoption of MIV alone would have significantly increased (at 10%) rice yields by 0.3 t/ha (16.6%). Likewise, the joint adoption of MIV and chemical fertilizers would have significantly increased (at 1%) rice yields by 0.91 t/ha (48.5% increase) in comparison with the non-adopters' group. Adopting only chemical fertilizers would not have had a significant effect on rice yields.

Once the potential endogeneity of the adoption of rice technologies is controlled for, the estimates of the impacts on rice yields change. Although we still found a positive effect of adopting only MIV, the effect is no longer statistically different

TABLE 4 Marginal effect estimates for multinomial logit (MNL) model of technology adoption.

Variables	(1) No adoption	(2) Improved varieties (IV)	(3) Fertilization	(4) IV + fertilization
Farm size (Log scale)	−0.091*** (0.021)	0.011 (0.018)	0.007 (0.010)	0.073*** (0.013)
Share of rice within the farm (%)	−0.003*** (0.001)	0.001** (0.001)	0.001** (0.000)	0.001** (0.001)
Member of a farmer association (1 = yes)	−0.141** (0.061)	0.083 (0.071)	−0.021 (0.034)	0.079** (0.032)
Received extension services (1 = yes)	−0.055 (0.050)	−0.001 (0.055)	0.032 (0.027)	0.024 (0.029)
Received credit for purchasing agricultural inputs (1 = yes)	−0.152** (0.068)	0.047 (0.060)	0.031 (0.028)	0.074** (0.031)
Distance to San Juan de Yapacaní (log scale)	−0.001 (0.020)	−0.005 (0.013)	0.002 (0.008)	0.004 (0.013)
Schooling of the head of the household (years)	−0.009* (0.005)	0.010** (0.005)	−0.003 (0.003)	0.002 (0.003)
Age of the head of the household (years)	−0.001 (0.002)	0.002 (0.001)	0.001 (0.001)	−0.002* (0.001)
Off-farm income in the household (1 = yes)	−0.004 (0.035)	−0.024 (0.033)	−0.002 (0.019)	0.029 (0.024)
Income from animal sales and by-products (1 = yes)	0.074** (0.036)	−0.039 (0.038)	−0.013 (0.025)	−0.022 (0.025)
Observations	775	775	775	775
Department controls	Yes	Yes	Yes	Yes

Clustered standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.
Source: elaborated by the authors.

TABLE 5 Estimated impact of different technological adoptions on paddy rice yields.

Treatment	(1) Yield	(2) Yield (log)	(3) Yield	(4) Yield (log)
Modern improved varieties (MIV)	0.300* (0.163)	0.166** (0.084)	0.959 (1.463)	0.631 (0.841)
Fertilization	0.049 (0.229)	−0.117 (0.157)	−1.473 (1.225)	−1.049 (0.790)
MIV + fertilization	0.911*** (0.218)	0.485*** (0.107)	1.815** (0.833)	1.030** (0.448)
Constant	1.889*** (0.096)	0.376*** (0.068)	1.672*** (0.353)	0.227 (0.219)
Observations	775	775	775	775
Method	OLS	OLS	TSLS	TSLS

Robust regression test (endogeneity test suggested by Wooldridge, 1995), $F_{(3,92)} = 2.59627$ ($p = 0.0571$), Kleibergen-Paap rank chi-square statistic: 2.80 (p-value: 0.08).
Bootstrap standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.
Source: elaborated by the authors.

from zero. Likewise, we continued to find a statistically insignificant effect of the adoption of only chemical fertilizers on rice yields. However, the adoption of MIV and chemical fertilizer jointly would increase more than double the expected rice yields, with a potential increase of roughly 1.67 t/ha (103% increase) compared with those without rice technology. As the endogeneity (Robust regression, Wooldridge, 1995) and the under-identification (Kleibergen-Paap rank statistic) tests rejected their null hypothesis, we prefered the results of the TSLS specification.

Our results are consistent with previous findings that the decision to jointly adopt a package of agricultural technologies has a significant and large effect on crop productivity in comparison with the adoption of individual crop technologies or the non-adoption (Teklewold et al., 2013; Kassie et al., 2015; Khonje et al., 2018; Shafiwu et al., 2022). While there is evidence that genetic improvement by itself could bring a variety of productivity and welfare impacts (Arouna et al., 2017; Zeng et al., 2017; Wossen et al., 2019; Sellitti et al., 2020), some studies have reported that the adoption of only improved crop varieties has not yielded some of the expected impacts due to heterogeneous profitability on adopting improved varieties in Kenya (Suri, 2011), unsustainable rainfall to keep the advantage of NERICA rice varieties in Uganda (Kijima et al., 2011), or inability to show their full potential due to absence of major stresses during the evaluation period (Mills et al., 2022).

An increasing number of studies are providing evidence of much larger impacts coming from complementary crop technologies that are made available as packages to small farmers (Emerick et al., 2016; Tabe-Ojong et al., 2023). These findings support efforts to improve agricultural extension and technical assistance for smallholders in different regions aiming at achieving expected impacts (Berhane et al., 2018; Hörner et al., 2022). In Bolivia, there is a group of agricultural development initiatives that are trying to identify the right mix of agronomic practices to support small farmers. Preliminary reports suggest that crop yields could more than double due to these technology packages (World Bank, 2018). However, this needs to be confirmed with a more rigorous evaluation approach.

Although we were unable to estimate the impacts of the adoption of rice technologies on rice income, comparing the PPI and HDDS between adopters of one technology, adopters of both technologies, and non-adopters provides an indication of the effect of technology adoption on welfare indicators (Table 6). The PPI measures the probability that a household falls under the Bolivian poverty line in 2013–2014, while the HDDS is a dietary diversity index that captures the number of food groups consumed by all household members in the same period of time. We found that non-adopters of either chemical fertilizers or MIV are at a disadvantage compared to adopters of these technologies in both indicators. Adopting only chemical fertilizers correlates with an 8.6% point reduction in the probability of falling under the poverty line. Furthermore, adopting only MIV reduces this probability by 13.5% points, and adopting both technologies implies a reduction of 19.8% points. Likewise, farmers adopting one or both technologies simultaneously are better off in terms of dietary diversity than non-adopters.

While our study documented a relatively low joint adoption of improved rice varieties and chemical fertilizers, our findings also revealed the potential benefits for future scaling-up strategies. Although roughly less than a fifth of Bolivian rice producers are joint adopters of MIV and chemical fertilizers, partial adoption of one of these technologies already occurs in 37% of farmers. To boost the adoption of packages of rice technologies, the rice sector could rely on mechanisms for the widespread dissemination of such technologies, like in the case of vouchers for agricultural inputs (Salazar et al., 2015).

Bolivia has enormous potential for significantly boosting rice yields through the promotion of packages of rice technologies. Currently, Bolivia's production conditions with a predominance of rainfed agriculture are similar to Brazil's situation 20 years ago. However, improving the small farmers' access to packages of rice technologies as Brazil did (Fitz-Olivera and Tello-Gamarra, 2022) could significantly increase rice production. This would not only allow Bolivia to achieve the desired self-sufficiency in rice production but, like many other Latin-American countries, also become an important exporter of rice (Fitz-Olivera and Tello-Gamarra, 2022) and contribute to Global Food Systems.

5. Conclusion

In this article, we studied how Bolivian farmers make adoption decisions for complementary rice technologies and then examined the potential impact of this adoption on rice yields. As in most Latin-American countries, different improved rice technologies have been made available to rice farmers in Bolivia. However, the adoption of these technologies remains constrained, and rice yields are among the lowest in the region. We aim to better understand the adoption of improved rice varieties and chemical fertilizers when both technologies are made available simultaneously.

Taking advantage of a nationally representative plot and household survey of 775 rice growers in Bolivia and using a multinomial logit model and optimal instrumental variable approach, we report significant and strong impacts of the joint adoption of improved rice varieties and chemical fertilizers. Once we controled for the potential endogeneity of the decision to

TABLE 6 Comparison of some welfare measures across different adoption packages.

	Poverty probability index	Std. dev.	Difference in means	Std. error	Household dietary diversity score	Std. dev.	Difference in means	Std. error
Overall	48.17	29.05	–	–	10.51	1.34	–	–
No adoption	56.06	27.97	–	–	10.19	1.4	–	–
Modern improved varieties (MIV)	42.48	29.26	−13.58***	3.33	10.57	1.29	0.35**	0.15
Fertilization	47.47	28.38	−8.6**	4.15	11.08	1.11	0.86***	0.17
MIV + fertilization	36.22	25.68	−19.84***	3.70	10.98	1.09	0.76***	0.14

The table reports the average Poverty Probability Index (PPI) and Household Dietary Diversity Score (HDDS) within every group. The PPI reports the probability that a household falls below the national poverty line, while the HDDS is a count variable referring to the number of food groups consumed by the household's members in the 24 h prior to the survey. Difference in means is the OLS coefficients (with associated standard errors) of the regression of either PPI or HDDS on three dummy variables indicating whether the observation is on a specific group (i.e., adopts a single specific practice or both), thus capturing the difference with respect to those who do not adopt any technology ($N = 775$). Standard errors are clustered at the village (community) level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

adopt rice technologies, we found that adopting only improved rice varieties or adopting only chemical fertilizers does not significantly affect rice yields; nevertheless, by exploiting the complementarities of these two technologies, the joint adoption of MIV and chemical fertilizers, more than double rice the yields.

Although we were unable to estimate the impacts of the adoption of improved rice varieties and chemical fertilizers on rice income, we found that adopting these technologies is correlated with a reduced probability of Bolivian households falling under the poverty line and with a higher dietary diversity index. Adopting both technologies simultaneously has an even stronger positive effect. Future studies should put more emphasis on addressing the limited bookkeeping among Bolivian farmers to collect reliable data on input use and cost. This would allow us to better estimate rice and farm income and the variable cost of using different technologies.

Based on these research findings, we highlight the implications on rice production and the potential contribution to the Global Food System of the joint adoption of rice technologies. Our results support more recent strategies to promote packages of agricultural technologies instead of single technologies within extension services for small farmers. In countries like Bolivia, where the majority of rice production still relies on rainfed cropping systems, exploiting the complementarities for different technologies may not only increase the adoption of these technologies but also boost rice yields to levels that are comparable to other Latin-American countries producing rice under similar conditions. As this has been the rice development pathway observed in these neighboring countries, broader dissemination of rice technologies has the potential to make Bolivia achieve self-sufficiency in rice production and become a net exporter contributing to Global Food Systems. Future studies that collect additional and more complete rounds of data should be able to confirm this article's findings.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

The conception and design of the study were contributed by JM and RL. Material preparation and data collection were done by RL and CG. Analysis and the first draft of the manuscript were written by JM and RL. The manuscript was reviewed by all authors and edited by RL. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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