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Ecological intensification and sustainable intensification: Increasing benefits to and reducing impacts on the environment to improve future agricultural and food systems

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Ecological intensification and sustainable intensification: Increasing benefits to and reducing impacts on the environment to improve future agricultural and food systems

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Editorial:Ecological intensification and sustainable intensification: increasing benefits to and reducing impacts on the environment to improve future agricultural and food systems

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Editorial on the Research Topic
Ecological intensification and sustainable intensification: increasing benefits to and reducing impacts on the environment to improve future agricultural and food systems

Sustainable agricultural systems are pivotal to future agriculture's capacity to support the projected global population of 9 billion people by 2050. Future agricultural food systems must effectively tackle pressing sustainability challenges that adversely affect both food production and the environment. These challenges encompass heightened land demand, sustainable use of synthetic nitrogen, declining soil carbon pool, and biodiversity loss. This Research Topic collection highlights different approaches to improving the environmental sustainability of agricultural systems around the world. Changes in climate require regional to farm-level approaches to climate change adaptation. From 2009 to 2018, maize production in China has been impacted by changes in climate but this is regionally dependent (Zhang et al.). Strategies to reduce agriculture's environmental impact also depend on the region evaluated and the farm or agricultural stakeholder group involved. Within this context, the concepts of sustainable intensification (SI) and ecological intensification (EI) play important roles (Figure 1). SI of agricultural systems involves more efficiently using resources in order to spare future degradation of natural habitat. Meanwhile, EI diversifies farming systems which can not only improve agricultural production, but also enhance agro-ecosystems.

Typically, SI involves specific changes to component(s) of specialized conventional agricultural systems such as encouraging water conservation, adopting low-carbon agriculture, and increasing the efficiency of inputs used on-farm. Water conserving irrigation adoption in drier agricultural regions such as Iran's Fars province with networks of reservoir and canals was low among surveyed farmers (37%), but could be improved by reducing the interest rate paid for such capital

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investments from the current 18%–8% (Mirzaei et al.). Low-carbon agriculture adoption potential is influenced by regional support networks. Central and western regions in China, which are more rural and less connected to other regions, require more support than eastern China which has more developed networks, a more central network position relative to other regions, and more control over resources used for low-carbon agriculture (Fang et al.). The ecological efficiency of input use can be enhanced by using agricultural inputs such as nitrogen fertilizers and fungicides with less adverse environmental impacts. Use of older machinery results in higher fuel consumption and greenhouse gas emissions. Najafabadi et al. modeled such ecological efficiency increases using data envelope analysis (DEA) and the material balance principle (MBP) applied to a slacks-based measure (SBM) model for saffron production in Iran.

EI can be adopted for both settled agriculture and shifting cultivation. Zhao et al. found adoption of green agricultural technologies (e.g., physical control technology, pollution-free pesticides, soil formula fertilization, agricultural film for water conservation, water/fertilizer integration technology, grafting) for smallholder farmers relocated due to construction of the Three Gorges Reservoir are positively associated with adoption of e-commerce to market and sell agricultural products. This was based on 688 surveyed re-settlers with 37.7% adopting four or more of these six green agricultural technologies. Long-term hay and maize rotations in Vermont, USA from 2009 to 2021 analyzed by White et al. suggest that environmental goals can be balanced with maintaining adequate crop yield. In this long-term experiment, continuous corn, a short rotation (4 years hay, 6 years corn), and a long rotation (8 years hay, 2 years corn) were evaluated. Here, the short rotation did not significantly reduce corn dry matter yields. Meanwhile soil organic matter, respiration, aggregate stability, and forage crude protein increased compared to continuous corn, especially with more years of hay in the rotation. However, active carbon and forage digestibility were lower for corn-hay rotations compared to continuous corn.

Shifting agriculture (i.e., swidden) is an older method of agricultural production where small areas in the forest are burned for short-term agricultural production and after farming is abandoned, the area is reclaimed by forest as other areas are used. However, the area selected can have significant implications in reducing or increasing adverse environmental impacts. For example, in northern Thailand, lower slope for burned areas in shifting agricultural production was associated with less soil loss and more soil organic carbon and nitrogen, electrical conductivity, as well as exchangeable magnesium and calcium (Arunrat et al.). Therefore, swidden in flatter areas can improve environmental sustainability.

EI can also be used to diversify farm enterprises and to preserve high conservation value areas. Total green factor productivity can be associated with enterprise diversification such as agro-tourism. Wang et al. documented greener, circular agricultural productivity is associated with agro-tourism in China based on data from 30 province-level administrative divisions from 2008 to 2019. Preservation of high conservation value areas can use jurisdictional approaches, taking into account environmental metrics to prioritize areas for conservation. In a case study jurisdiction in Indonesia, Padmanaba et al. show greater coordination between government agencies is required at different jurisdictional spatial scales in order to define high conservation value areas outside of oil palm plantations in native forests.

The findings of these studies suggest that making informed choices when selecting tools and equipment, implementing alterations in land-use patterns, and adopting innovative management practices/processes

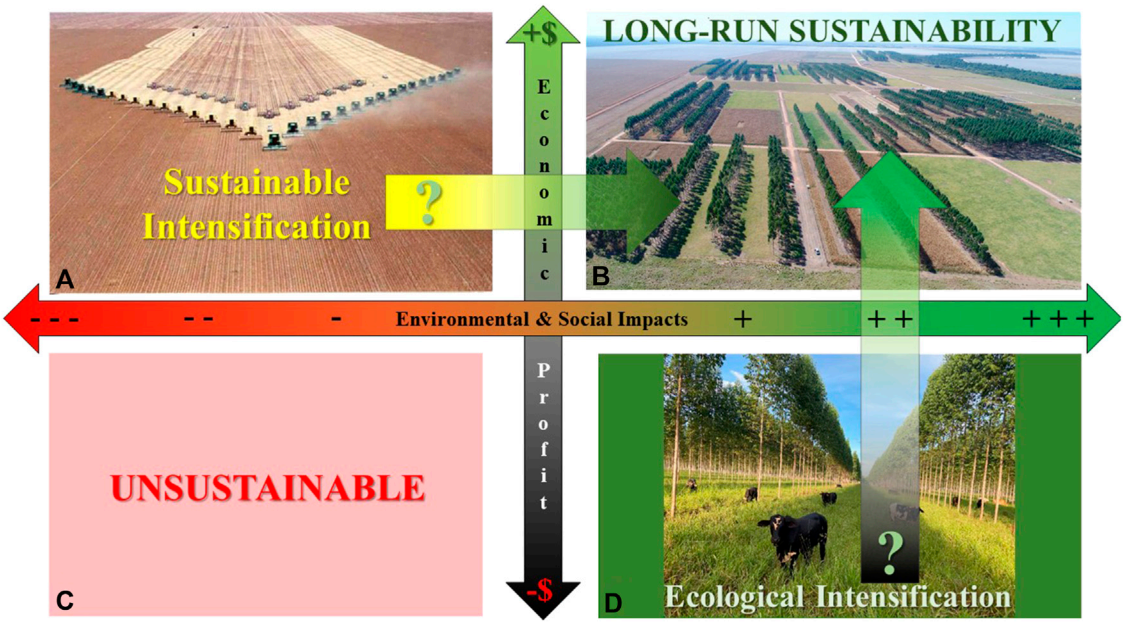

FIGURE 1
Economics versus environmental impact of **(A)** sustainable intensification pathway to **(B)** long-run sustainability, **(C)** unsustainable agricultural systems, and **(D)** ecological intensification and pathway to **(B)**. Pictures provided by Gabriel Rezende Faria, a journalist and public relations officer at Embrapa, Brazil.

that minimize environmental harm are not only feasible but also pivotal steps toward achieving collaborative, sustainable, and resilient regional food systems. Embracing EI and employing appropriate SI approaches both play a pivotal role in environmental sustainability and global food security. To ensure success, it is imperative to disseminate accurate information to stakeholders at the right stages of agricultural operations. Proactive communication is essential for reducing overuse of both natural and synthetic resources, which could otherwise lead to further detrimental environmental effects.

Additionally, effective collaboration between research organizations and government or private entities is crucial for establishing poignant guidelines, regulations, and policies that facilitate sustainable transitions. Public policies such as government subsidies can incentivize the technologies/practices showcased in this Research Topic for SI/EI enhancements. This collaborative effort is influential in achieving SI and EI strategies that can yield positive outcomes for both society and the environment, help mitigate existing negative impacts, prevent further depletion of soil organic carbon, restore ecological equilibrium, and enhance biodiversity. These practical strategies combined with public policy support can help achieve the ambitious goal of global food security by 2030.

Author contributions

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The impact of climate change on maize production: Empirical findings and implications for sustainable agricultural development

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Continuous warming climate conditions have triggered numerous extreme weather events, exerting an unprecedented impact on agricultural and food production. Based on the panel data of 3,050 small farmers engaged in maize planting from 2009 to 2018 and collected by the National Rural Fixed Observation Point in China, this study uses the Transcendental Logarithmic Production Function model to estimate the impact of temperature, precipitation, and sunshine hours on maize output. Further, considering climate condition heterogeneity, this study analyzes the development potential of five major maize production areas in China. Results show that temperature and precipitation have a positive impact on maize output and that insufficient sunshine hour is an obstacle to the growth of maize output. Five major maize production areas are affected by climate condition differently, entailing the need for tailored response measures. Additionally, land, labor, and material capital input are key factors affecting maize output. Based on conclusion, we put forward the following suggestions to promote sustainable agricultural production, including strengthening the prediction of temperature, precipitation, and sunshine hours in major maize production areas, optimizing the agricultural production layout and the planting structure based on local endowment, enhancing farmers' adaptive behavior training toward climate change, developing irrigation and water conservation projects.

KEYWORDS

climate change, maize output, major production area, transcendental logarithmic production function, coping measures

1 Introduction

The global temperature has been rising in recent decades and climate warming has been accelerating. Continuously warming climate conditions have also triggered more extreme weather events that affect agricultural production, which is highly sensitive to natural resources (Crost et al., 2018). Research suggests that climate change is placing great pressure on agricultural production (Wilson et al., 2022). Under the stress of climate change, food production has been facing prominent negative shocks (e.g., the increase in disaster areas and food production reductions), which may lead to hunger and malnutrition. Thus, these issues have been catapulted into the forefront of international discussions across numerous countries. Indeed, researchers propose that various countries urgently need to look for effective strategies to address the adverse effects of climate change, such as promoting the training for farmers on climate change adaptation behaviors (Moore and Lobell, 2014), enhancing the irrigation facilities (Aragón et al., 2021), and further developing a "climate-smart food system" (Wheeler and von Braun, 2013).

China is one of the countries most affected by climate disasters. Meteorological changes and extreme weather adversely affect China's agricultural production and have a negative impact on agricultural total factor productivity and input utilization rate. Global warming has also caused huge economic losses to the country's grain output (Chen et al., 2016). Furthermore, China is one of the most populous countries in the world. According to the data of National Bureau of Statistics of China, in 2020, the national population reached 1.41 billion, accounting for about 18% of the world's total population. Feeding more than one billion people entails many problems, and solving these problems is important for both the national economy and people's livelihoods. Accordingly, the impact of climate change on the food supply in China cannot be ignored. Furthermore, climate change's influence on agricultural output leads to changes in market prices, which impacts the livelihood of agricultural producers and causes social problems. From this perspective, assessing the impact of climate change on agricultural production is of great significance for studying the relationships among climate change, agricultural product supply, market prices, and other economic issues, as well as for effectively formulating policies to tackle climate change (Aragón et al., 2021; Filho et al., 2022; Oyinlola et al., 2022; Wheeler and von Braun, 2013).

Recent research on the effects of climate change on food production mainly focus on natural and economic aspects. Regarding the research on natural aspects, they mainly focus on how to build crop models for the dynamic simulation of crop growth and on the impact of climate change on crop growth (Hasegawa et al., 2022; Hawkins et al., 2013; Tonnang et al., 2022; Wang et al., 2022). Nonetheless, these studies require many hypothetical parameters to be set, which may lead to uncertain evidence (Carr et al., 2022). This may be the limitation of research in this field. Regarding the research focusing on economic aspects, for example, Lin et al. (2011) used household data and a nonlinear production function model to calculate the output elasticity of changes in temperature, precipitation, and average sunshine hours for three major food crops. In the United States of America, Coffel et al. (2022) calculated the output elasticity of changes in temperature, precipitation, and sunshine for maize and soybean crops. In China, Song et al. (2022) calculated the economic impact of climate change on maize yields based on the Ricardian model. Despite these studies providing valuable insights, they didn't reach a consistent conclusion owing to differences in data sets and methods. Other researchers show that farmers can adjust their behavior to adapt to climate change by collecting relevant information on the topic (Tazeze et al., 2012). Based on these remarks, some scholars discuss the influencing factors and effectiveness of farmers' measures to deal with climate change from the perspective of farmers' subjective initiatives (Huang et al., 2015; Rijal et al., 2022; Shariatzadeh and Bijani, 2022; Zobeidi et al., 2022).

These research highlights the significance of current studies, mainly focusing on maize. According to the data of National Bureau of Statistics of China, maize is the largest grain crop regarding sowing area and output in China. Maize is also an important feed and industrial raw material (Shukla and Cheryan, 2001; Klopfenstein et al., 2013). With the rapid development of China's economy, the dietary structure of national residents has changed and the demand for meat has increased rapidly, stimulating the development of animal husbandry and the "rigid" growth trend of feed grain demand (Shimokawa, 2015; Fukase and Martin, 2016). Accordingly, it is of great practical significance to provide data for stakeholders that enables them to effectively ensure maize output, reasonably plan maize production areas according to local conditions, and optimize the allocation of agricultural resources.

The above research has mainly given us the conclusion about climate change's influence on the agricultural output from the regional level. However, few relevant studies have explored the impact of climate change on China's maize output using a national scale panel data comprising data at the micro level (e.g., farmer household level). Compared with previous studies that assess the impact of climate change based on a regional level, it is more meaningful to study the impact of climate change from the farmers' perspective. Farmers are the main body most directly affected by climate change, especially for developing countries like China, where small farmers are the main body. Whether farmers can respond to climate change in a timely and effective manner is crucial. Therefore, exploring the impact of climate change on maize output at the farmer household level can more accurately project the actual impact of climate change on agricultural output in developing countries. This paper uses a nationally representative farmer household-level panel data and employs the fixed-effect model to control for time-invariant factors, such as the management ability of agricultural producers, the quality of household contracted farmland and other factors to more accurately identify the impact of climate change on maize output.

Accordingly, using data including 3,050 small farmers engaged in planting maize for 10 consecutive years from National Rural Fixed Observation Point of China, and based on the macro-overview of China's maize production and climate change, this study first tests the impact of temperature, precipitation, and sunshine hours on farmers' maize production at the national level. Then, the heterogeneous characteristics of the climate conditions of the five major maize production areas in China are considered, and the methods to stimulate the future development potential of maize in each production area are employed. Finally, relevant countermeasures and suggestions are presented.

2 Maize output change and climate change in China

2.1 Output change in the five major maize production areas in China

Maize has a variety of uses in the grain, economics, forage, fruit, and energy fields. It is a grain crop with the longest industrial chain in China and holds a great strategic significance for the country. From 2009 to 2018, maize output increasing from 163.97 to 257.17 million tons (growth rate: 56.84%) in the country (Supplementary Table A1). Maize is playing an increasingly prominent role in the national agricultural production.

Furthermore, this grain crop is widely planted across 31 provinces (autonomous regions and municipalities) of China. In fact, by combining *The Atlas of Growth Periods of Major Crops in China* with the available data, the country can be divided into the northern spring sowing maize area (hitherto Production area 1), HuangHuai Plain spring and summer sowing maize area (hitherto Production area 2), southwest hilly maize area (hitherto Production area 3), southern hilly maize area (hitherto Production area 4), and northwest inland maize area (hitherto Production area 5).

Supplementary Table A1 shows that Production area 1 is the largest maize production area in China, accounting for nearly 50% of the country's total maize output. From 2009 to 2018, its maize output shows an increase from 67.17 to 119.64 million tons (growth rate: 78.12%). Production area 2 is the second-largest maize production area, accounting for approximately 30% of the country's total maize output. From 2009 to 2018, its maize output shows an increase from 58.53 to 80.19 million tons (growth rate: 37.01%). In the other production areas, the total maize output accounted for approximately 20% of the total output during this same period, as well as show an increase from 38.26 to 57.36 million tons (growth rate: 49.89%). Overall, China's maize shows a steady output increase over the analyzed period, with slight fluctuations across the years.

2.2 Climate change in the five major maize production areas in China

Generally, human activity relies on the natural environment, and agriculture is one such activity that is highly sensitive to climate change. Therefore, the impact of climate change on maize output cannot be ignored. Temperature, precipitation, and sunshine are basic elements of the climate, as well as key factors affecting maize output. The abnormal temperature and water imbalance due to abnormal climate conditions have different effects on maize growth. With the available data, Supplementary Tables A2–A4 show the changes in temperature, precipitation, and sunshine hours in the five major maize production areas of China.

Supplementary Table A2 shows that from 2009 to 2018, the monthly average temperature is the highest in Production area 4 (16.88°C) and the lowest in Production area 1 (7.81°C). Further, Production areas 3, 2, and 5 show an monthly average temperature of 16.15°C, 12.95°C, and 9.95°C, respectively. Supplementary Table A3 shows that from 2009 to 2018, the monthly average precipitation is the highest in Production area 4 (98.92 mm) and the lowest in Production area 5 (29.33 mm). Further, Production areas 3, 1, and 2 show a monthly average precipitation of 86.37, 51.36, and 49.27 mm, respectively. Supplementary Table A4 shows that from 2009 to 2018, the monthly average sunshine hour is the highest in Production area 5 (206.59 h) and the lowest in Production area 3 (125.62 h). Further, Production areas 1, 2, and 4 show monthly average sunshine hours of 195.62 h, 188.58 h, and 135.07 h, respectively.

In summary, Production area 1 has longer sunshine hours, average precipitation levels, and the lowest temperature over the analyzed period. Production area 2 has average temperature, sunshine hours, and less precipitation. The temperature and precipitation conditions in Production area 3 are high, but sunshine hours are the lowest. Production area 4 has the highest temperature and precipitation conditions, but sunshine hours are shorter. Finally, Production area 5 has the longest sunshine hours, cooler temperatures, and less precipitation.

3 Model settings and data source

3.1 Model setting

Theoretically, input factors are key elements affecting maize output, and they include land input, labor input, and material inputs (e.g., seeds, fertilizers, pesticides, agricultural film, agricultural machinery, and irrigation). Land is the material basis for maize growth, and in theory, the sown area has an important positive impact on maize output. Labor is also an important factor affecting maize output. In this study, the number of working days is used as an indicator of labor input in maize output. Materials are the main input factors for maize output, and upon considering that the quantity of different types of materials is not comparable, we used total costs to reflect material input in maize output.

Based on previous research (Jones and Thornton, 2003; Lobell and Asner, 2003; Lin et al., 2011), crop growth is affected not only by the input of production factors but also by climate change. Hence, maize growth results from the joint action of sunshine hours, temperature, precipitation, and other factors. Although these factors are not directly invested in maize production, they affect the efficiency of the production factors.

In addition, researchers have shown that there may be a quadratic relationship between climate factors and grain crop output (Kabubo-Mariara and Karanja, 2007; Schlenker and Roberts, 2009; Adhikari et al., 2015). A Cobb-Douglas production function calculates the relationship between production output and inputs (factors), which is used to predict technological change (Zellner et al., 1966). Compared to C-D production function, Translog production function may be more general and flexible, which has been widely applied to the area of agricultural production accounting. Compared to the fixed elasticity of various input factors and output in C-D production function, Translog production function can relax this hypothesis, thereby more accurately estimating the impact of climate change on agricultural output.

In this paper, controlling for the fixed effects of farmer household and year, two-way fixed-effects model is used to evaluate the impact of temperature, precipitation, and sunshine hour variation on maize output. Farmer household fixed effect denotes the farmer household-level time-invariant unobservable factors which may be related to maize output, such as farmer's labor capacity and cropland quality; Year fixed effect denotes the time-variant factors, including the other climate and social factors. In summary, we constructed a transcendental logarithmic production function of variable elasticity that is easy to estimate and highly inclusive, as shown in Eq. 1:

$$\begin{aligned} LnY &= \alpha_0 + \alpha_1 LnS + \alpha_2 LnL + \alpha_3 LnK + \frac{\alpha_4}{2}(LnS)^2 + \frac{\alpha_5}{2}(LnL)^2 \\ &+ \frac{\alpha_6}{2}(LnK)^2 + \alpha_7 LnS \times LnL + \alpha_8 LnS \times LnK + \alpha_9 LnL \times LnK \\ &+ \alpha_{10} LnTe + \alpha_{11} LnRa + \alpha_{12} LnSu + \frac{\alpha_{13}}{2}(LnTe)^2 + \frac{\alpha_{14}}{2}(LnRa)^2 \\ &+ \frac{\alpha_{15}}{2}(LnSu)^2 + \alpha_{16} T + \mu \end{aligned} \tag{1}$$

where Y is a farmer's total maize output; S is the farmer's sown area of maize; L is the number of working days for maize production; K is the material cost for maize production; Te is the temperature condition (°C); Ra is the precipitation condition (mm); Su is the number of sunshine hours; and T is the time trend variable. We selected a two-way fixed-effects panel data model for the analysis.

Notably, following previous literature (Rurinda et al., 2015; Ureta et al., 2020; Wu et al., 2021), there are multiple reasons to use maize output rather than maize productivity as dependent variable. First, China's small farmer households are still the main body of cropping maize, and their production decisions are mainly based on maize planting area and output (Huang and Ding, 2016). Thus, using maize output is more in line with Chinese farmers' production condition. Second, in Translog production function, maize planting area has been absorbed as land input factors, which also helps to better estimate maize output.

Since this study focuses on the contribution of different factors to maize output changes, we also calculate the contribution of factor changes to maize output changes by obtaining the output elasticity of factors (i.e., the ratio of output increases when factor input increases by 1%, while other conditions remain constant).

3.2 Data sources

For the empirical analysis, we use farmer household-level data from the National Rural Fixed Observation Point. The National Rural Fixed Observation Point are a micro-level panel data set based on farmer households. The survey began in 1986 and now covers 31 provinces (autonomous regions and municipalities), 368 counties, 375 sample villages, 23,000 account-keeping agricultural (pastoral) households, and more than 1,600 new agricultural management subjects. The survey covers all aspects of farmers' production, operation, consumption, and investment. Especially in grain production, detailed and reliable survey records are available for the output, sown area, and expenditure of related inputs of each crop. We selected farmers who had been producing maize for 10 consecutive years (from 2009 to 2018) as the sample for the empirical analysis, totalizing 3,050 households. The climate data sources are the monthly data of the China National Meteorological Observatory from 2009 to 2018, which is provided by the China Meteorological Science Data Sharing Network. According to the coordinates of the county center point and the meteorological observation point, based on the principle of the shortest spatial distance, the connection between the farmer household data set and the meteorological data set is realized. It should be stated that we use maize growing season data (The growing season of Production area 1 is from May to October; the growing season of Production area 2 is from June to October; the growing season of Production area 3 is from March to September; the growing season of Production area 4 is from March to August; the growing season of Production area 5 is from April to September).

The main variables and their meanings are shown in Supplementary Table A5. Farmers' average total maize output is 4,587 kg. Regarding inputs, farmers' average sown area of maize is 8.24 mu, labor input is 59.92 days, and material input is 2,251.71 yuan. Regarding climate, during growing season the monthly average temperature in the area where the sample farmers are located is 20.65°C, the monthly average precipitation is 97.15 mm, and the monthly average sunshine hours are 188.14 h.

4 Results

4.1 Analysis of estimated results

4.1.1 Estimation results of the model of influencing factors of maize output

For estimations using the 10-year farmer household panel data set, we use a two-way fixed-effect model regression method. Missing variables and time changes are controlled as much as possible (through individual fixed-effects and time fixed-effects, respectively) to identify the impact of climate change more accurately on maize output. Supplementary Table A6 presents the results of the influencing factor model for maize output. The adjusted R^2 of the entire model is 0.8962, indicating that the independent variables explain 89.62% of the dependent variables. In addition, we also conducted an over identification test and rejected the assumption of using the random-effect model.

Furthermore, as shown in Supplementary Table A7, the mean values of output elasticity of land, labor, and material input (main input factors) are 0.6740, 0.0531, and 0.2470, respectively. That is, for every 1% increase in land, labor, and material input, maize output increases by 0.67%, 0.05%, and 0.25%, respectively. Overall, land inputs (sown area) remain the most important factors affecting maize output, followed by material and labor inputs. With the continuous development of society and the economy, the problems of non-agricultural land competition, non-grain use of farmland, and land abandonment have become increasingly prominent. Further, industrial and domestic pollution have led to a decline in the quality of arable land and to a small number of farmlands with high and stable outputs. Therefore, great importance should be attached to stabilizing grain cultivation areas. Simultaneously, under the influence of economic laws, the opportunity cost of labor for agricultural production continues to increase, and more farmers choose to work to increase their income. On the one hand, this leads to reduced labor input; on the other, this leads to a more aged and feminized labor force (Palacios-López and López, 2015; Liu et al., 2019; Rigg et al., 2020), which in turn reduces the quality of labor input and is not conducive to maize output improvements. In addition, researchers have thoroughly demonstrated the important role of agricultural capital investment in promoting agricultural technological progress, meaning that an increase in physical capital plays an important role in promoting agricultural output (Binswanger and Rosenzweig, 1986; Smith, 2004; Syed and Miyazako, 2013).

Regarding climate factors, temperature, precipitation, and sunshine hours have significant effects on maize output, meaning that climate change will increase maize output fluctuation. The output elasticities of temperature, precipitation, and sunshine hours are 0.3940, 0.0153, and −0.0515, respectively (Supplementary Table A7). As maize is a temperature-loving crop, it is very sensitive to temperature fluctuations, with an increase in this variable being beneficial for maize output. Precipitation has a significant positive impact on maize output, indicating that an appropriate increase in precipitation levels can also increase maize output. From the model results, the output elasticity of sunshine hours is negative, meaning that there is insufficient lighting to some extent.

4.1.2 Contribution of various factors to maize output growth

In this section, the output elasticity of each factor is multiplied by the change rate of the factor within the sample year, and then divided by the change rate of maize output within the sample year. This serves to express the contribution of factors to maize output. The results are presented in Supplementary Table A7.

Supplementary Table A7 shows the contribution of input and climate factors to maize output. Regarding input factors, the contribution rates of material, land, and labor input to maize output are 53.71%, 46.33%, and −3.47%, respectively. These results further illustrate the roles of land and material input in maize output, which is in line with previous literature (Sheng et al., 2019; Qiu et al., 2021). Regarding climate factors, the contribution rates of temperature, precipitation, and sunshine hours to maize output are 2.20%, 0.58%, and −0.51%, respectively, indicating that these variables have limited contributions to maize output. This may be because of the high concentration of production in the analyzed areas. Specifically, Production areas 1 and 2 account for nearly 80% of the country's total maize output, and both are less affected by climate change. Therefore, it is necessary to further subdivide and understand the impact of climate change in each area to propose more effective measures to deal with climate change and ensure the supply of maize in China.

4.2 Heterogeneity test

Since China has a vast territory, different production areas have different natural conditions and socioeconomic characteristics. In the process of maize production, farmers are affected not only by their own characteristics (individual effects) but also by their living environment, that is, environmental background effects. Accordingly, this section further divides the sample into the five production areas, repeats the analyses, and focuses on the impact of climate factors on maize output. This serves to determine the characteristics of the impact of climate change on maize output in different production areas, grasp the future trend of maize production layout, and put forward targeted policy recommendations for stakeholders to reference. Supplementary Table A8 presents the model estimation results by area. The calculations for output elasticity of the climate factors in each area and their contribution rate to maize output growth (Supplementary Table A9) are based on the results described in Supplementary Table A8.

In Production area 1, the impact of climate factors on maize output is small, with temperature having a negative effect on the output elasticity and contribution to maize output. This is mainly because although Production area 1 has climate conditions that are very suitable for maize growth and unique climate resources, low temperatures and chilling damage are among the main agro-meteorological disasters affecting this area. Hence, temperature fluctuation is an important factor for changes in maize output. In most regions of Production area 1, the temperature in spring is relatively low, and there is the problematic phenomenon of "cold springs." Insufficient accumulated temperature leads to slow maize growth, indicating another important explanation for the negative output elasticity and contribution rate of temperature in this production area.

In Production area 2, output elasticities for precipitation and sunshine hours are negative, while the contributions to maize output for temperature and precipitation are positive. Production area 2 has a warm and semi-humid climate with abundant rainfall, providing sufficient conditions for crop irrigation. Accordingly, maize planting methods are more diverse in this area, and intercropping and multiple cropping can coexist. However, in two cycles of multiple cropping, the utilization of solar thermal resources was low, only early maturing maize varieties can be planted, resulting in a low maize output (Wang et al., 2020; Zhai et al., 2017; Zhai et al., 2021). In addition, owing to the high temperature and humidity in summer, Production area 2 is prone to diseases and insect disasters, which adversely affect its maize output.

In Production area 3, output elasticities for temperature and precipitation are positive, and the contributions to maize output for sunshine hours are negative. The topography of Production area 3 is relatively complex when considering its natural landscape. Specifically, mountains, hills, and plateaus account for more than 90% of the total land area. Accordingly, regional differences in ecological conditions are very large and production conditions are poor. Due to the high temperature and humidity in the growing season of maize in Production area 3, as well as the lack of sunshine in the area, the problems of pests and diseases tend to be more serious, and this situation is not conducive to maize output and crop quality. From this point of view, Production area 3 is not suitable for maize growth.

In Production area 4, output elasticities for temperature and precipitation are positive, and contributions to maize output for temperature is negative. Around 10°C is a suitable temperature for the growth and development of maize, but Production area 4 has a higher temperature and abundant rainfall, which are more suitable for rice cultivation. Accordingly, the climate conditions in autumn and winter in Production area 4 are more favorable for maize production.

In Production area 5, output elasticities for temperature, precipitation, and sunshine hours are positive, and contributions to maize output for sunshine hours is negative. Production area 5 is characterized by dryness, and precipitation depends mainly on the melting of snow or river irrigation systems in the region. This area also has the advantage of abundance in heat resources, having great potential for improving maize quality and increasing income. Still, it is necessary to ensure appropriate supply of irrigation water. Since the contribution of sunshine hours to maize output is negative in this area, attention should be paid to the selection of new maize varieties that are density-tolerant, high-output, drought-resistant, and suitable for machine harvesting.

5 Analysis of the changes in maize production in the five major production areas in China

This section analyses the climate conditions and maize production inputs and outputs characteristics in the five major production areas at the farmer household level from 2009 to 2018. It also investigates the future layouts of these five production areas and proposes targeted countermeasures and suggestions.

5.1 Changes in the input of production factors in the five production areas

Regarding land input changes, a horizontal comparison of production areas shows that the average maize sown area per household in Production area 1 (15.18 mu) is prominently higher than that in other areas, being 193.27%, 433.82.32%, 479.90%, and 295.38% higher than that in Production area 2, 3, 4, and 5, respectively. Then, a vertical comparison of production areas shows an overall upward trend from 2009 to 2018 for maize sown area per household. In Production areas 1, 2, 3, and 5, the average maize sown area per household in 2018 is 27.68%, 29.53%, 24.60%, and 25.71%, respectively, higher than that in 2009. The exception is Production area 4, as its average maize sown area per household diminished by 20.22% during this period.

Regarding labor force changes, a horizontal comparison of production areas shows that the average labor force input per household in Production area 1 is the highest, followed by Production areas 5, 2, 3, and 4. Vertical comparison of production areas shows an overall downward trend from 2009 to 2018 for average labor force input per household. In Production areas 1, 2, 3, and 4, the average labor force per household in 2018 is 29.09%, 25.79%, 6.10%, and 47.66%, respectively, lower than that in 2009. The exception is Production area 5, which shows an increase of 15.86% in the average labor force input per household during this period.

Regarding material input changes, a horizontal comparison of production areas shows that the average material costs of maize production per household in 2018 is the highest in Production area 1 (4,296.29 yuan), followed by Production areas 2 (1,359.00 yuan), 5 (1,237.92 yuan), 3 (577.79 yuan), and 4 (539.49 yuan). Vertical comparison of production areas shows an overall upward trend from 2009 to 2018 for average material cost of maize production per household, except for Production area 4 (the average material cost of maize production per household in 2018 is 0.03% lower than that in 2009). In Production areas 2, 3, 1, and 5, the average material cost of maize production per household in 2018 is 125.92%, 104.98%, 75.03%, and 64.61%, respectively, higher than that in 2009. Regarding the average cost per household, Production area 5 shows the smallest increase margin and Production area 1 shows the largest absolute value during this period.

5.2 Climate changes in the five production areas

Regarding temperature changes from 2009 to 2018, there is a rise in the monthly average temperature during the growing season in Production area 1 of 0.64°C (increase of 3.46%), and the temperature fluctuation is 0.23°C. For Production area 2, these values are 0.40°C (increase of 1.79%) and 0.34°C. In Production area 3, these values are 0.03°C (increase of 0.15%) and 0.25°C. In Production area 4, these values are 0.77°C (increase of 3.58%) and 0.50°C. In Production area 5, these values are 0.09°C (increase of 0.48%) and 0.28°C. In general, the temperature remained stable across areas with a relative upward trend, especially in Production areas 1 and 2, the two largest maize production areas in China. This temperature increase has advantages, such as the promotion of maize growth.

Regarding precipitation changes from 2009 to 2018, the monthly average precipitation during the growing season in Production area 1 increased by 20.90 mm (increase of 26.89%) with a standard deviation of 10.62 mm. For Production area 2, these values are −0.57 mm (decrease of 0.63%) and 11.90 mm. In Production area 3, these values are 34.90 mm (increase of 30.96%) and 14.31 mm. In Production area 4, these values are −13.18 mm (decrease of 9.82%) and 16.80 mm. In Production area 5, these values are 32.13 mm (increase of 91.62%) and 10.49 mm. In general, the precipitation in Production areas 1, 3, and 5 show an increase from 2009 to 2018, and this increase is significant in Production areas 3 and 5. Further, the increase in precipitation in Production area 3, which generally has sunny days, led to maize production damages. Therefore, measures need to be taken to deal with the difficulties related to pests and diseases caused by high precipitation. Nonetheless, in Production area 5, which generally has a relatively arid climate, the increase in precipitation is beneficial because it promotes the potential for greater local maize output. Meanwhile, the precipitation in Production areas 2 and 4 decreased slightly from 2009 to 2018, with more obvious fluctuations appearing in Production area 4.

Regarding sunshine hours changes from 2009 to 2018, the monthly average sunshine hours during the growing season in Production area 1 and 2, 7 years show numbers lower than those in 2009. In Production area 3, there is only 1 year with lower numbers. In Production area 4 and 5, there are 4 years with lower numbers. In general, sunshine hours in northern China are significantly higher than those in southern China during the period, and they are the highest in the northwest. Recently, due to human activity intensification, the decrease in sunshine hours has become more obvious. This emphasizes the need to develop reasonable planting structures that enable the full use of solar energy resources.

5.3 Maize output changes in the five production areas

Production factors and climate factors jointly affect maize output. A horizontal comparison of the production areas shows that climate factors in Production area 1 are suitable for maize crops, as well as that the land, labor, and material inputs are higher, leading to a high maize output. Specifically, in 2018, Production area 1 shows an average maize output per household of 9,610.43 kg, which is 237.59%, 739.14%, 1288.90%, and 384.15% higher than that of Production areas 2, 3, 4, and 5, respectively. This further verifies that production area 1 is the largest dominant production area. Production area 5 has the advantage of heat, and the increase in precipitation from 2009 to 2018 is conducive to solving the irrigation problems in the region; therefore, Production area 5 has great potential for maize output, albeit the small planting area per household is an obstacle.

A vertical comparison shows an upward trend for average maize output per household from 2009 to 2018. In Production areas 1, 2, 3, and 5, the average maize output per household in 2018 is 38.21%, 48.94%, 23.46%, and 61.76%, respectively, higher than that in 2009. The exception here is Production are 4, which shows a value in 2018 that is 32.74% lower than that in 2009. Based on the analyses in this section, it seems necessary to adjust the agricultural structure for maize production by local conditions. Further, for regions where the natural conditions are not suitable for maize cultivation, it is essential to emphasize their comparative advantages and improve agricultural production efficiency as much as possible.

6 Conclusion and countermeasures

Using micro-level household data of the National Rural Fixed Observation Point from 2009 to 2018, this study incorporates climate factors such as temperature, precipitation, and sunshine hours into the transcendental logarithmic production function and constructs a two-way fixed effect model. With the econometric model, then we empirically study the impact of climate change on maize output in China and the changes in farmers' maize production in different production areas. Furthermore, we analyse the developmental potential of each main maize production area in China. The main conclusion are as follows.

First, temperature, precipitation, and sunshine hours show significant effects on maize output. The output elasticity of temperature is 0.3940, that of precipitation is 0.0153, and that of sunshine hours is −0.0515. Maize is a crop that likes temperature and light and is most sensitive to temperature fluctuations. An appropriate increase in precipitation can also increase maize output, but there is the potential problem of insufficient sunshine hours that may also hinder output.

Second, temperature and precipitation generally positively contribute to maize output, and sunshine hours negatively contribute to maize output. The contribution rates of temperature, precipitation, and sunshine hours to maize output are 2.20%, 0.58%, and −0.51%.

Third, from a subregional perspective, different production areas are affected differently by the climate. Production area 1 has climate conditions that are very suitable for maize growth and is generally not greatly affected by climate, but attention should be paid to problems related to low temperature and chilling damage. The climate of Production area 2 is hot and humid in summer, easily leading to plant diseases, insect disasters, and adversely affecting maize output. The geomorphic environment of Production area 3 is complex, and in the growing season of maize, high temperatures are usually reported together with wet and rainy weather conditions, and these characteristics are not conducive to improvements in maize output and quality. The climate conditions of Production area 4 are suitable for rice production. Production area 5 is characterized by sufficient light for maize production, and it is also dry and has little precipitation; therefore, attention should be paid to ensuring the supply of irrigation water to maize crops.

Fourth, different production areas must take different measures to deal with climate change. Regarding temperature changes, the temperature conditions of the production areas are generally stable and show an upward trend from 2008 to 2019 in general. Regarding precipitation changes, the total precipitation in Production areas 1, 3, and 5 increased. Production area 3 experienced adverse impacts related to the increase, highlighting the necessity to strengthen pest control in the region. In Production area 5, nonetheless, higher precipitation can effectively alleviate the problem of droughts. Meanwhile, Production areas 2 and 4 show a decrease in precipitation levels over the studied period. Regarding sunshine hours changes, human activities have caused a reduction in sunshine hours, which are generally higher in the north than in the south; this emphasizes the need for the development of a reasonable planting structure and making full use of the available solar energy resources.

Fifth, land, labor, and material input remain key factors affecting maize output. Overall, the output elasticities of land, labor, and material input are 0.6740, 0.0531, and 0.2470, respectively. The opportunity cost of the labor force engaged in agricultural production is increasing, and material capital input has become an effective substitute for labor input. Different production areas have various divergent advantages, showcasing that the agricultural structure should be adjusted according to local conditions and agricultural production efficiency should be improved as much as possible.

Based on these conclusion, this study proposes relevant countermeasures and suggestions: In terms of the agricultural production layout, adjust the planting structure according to local endowments and match the local climate and economic condition during the process of crop selection. In terms of farmer's response to climate change, enhance technology training for farmers' adaptive behaviours toward climate change and minimize the damage to farmers from climate shocks. In terms of agricultural infrastructure constructure, develop farmland and water conservation projects and further strengthen irrigation facilities in areas with insufficient rainfall. In terms of sustainable agriculture development, prevent soil pollution and hardening from excessive application of pesticides and fertilizers and thereby ensure the planting area of maize and the cropland quality.

Data availability statement

The data is not publicly available and further inquiries can be directed to the corresponding authors.

Author contributions

Conceptualization, ZZ and MG; methodology, ZZ; software, JW; validation, JkL, ZZ, and JW; formal analysis, ZZ; resources, MG; data curation, JW and YJ; writing—original draft preparation, ZZ; writing—review and editing, JkL and WW; visualization, ZL and JL; supervision, MG; project administration, MG; funding acquisition, MG, ZZ, and JK. 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

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Spatial correlations and driving mechanisms of low-carbon agricultural development in china

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Low-carbon agricultural development in China is a prerequisite for rural revitalization and a key to achieving socio-economic green transformation. This paper used agricultural data from 30 Chinese provinces from 2001 to 2020, considering both carbon emissions from farming and livestock, agricultural low-carbon total factor productivity (ALTFP) was measured using the RSBM-GML index. Based on this, the network characteristics and driving mechanisms of low-carbon synergistic development in agriculture were explored with the help of an improved gravity model and social network analysis, and the dominant provinces in low-carbon synergistic development in agriculture are identified. The study revealed that the spatially linked network of ALTFP in China exhibits multi-threaded characteristics of spillover to non-adjacent provinces, and the whole network has a sparse structure and hierarchy. The eastern regions such as Beijing, Tianjin, Shanghai, Jiangsu, and Zhejiang are at the core of the network, with closer ties to other regions and a stronger role in allocating resources. While the western regions such as Xinjiang, Qinghai, and Gansu are located at the periphery of the network, with weaker access to the resources. Meanwhile, the spatial proximity of provinces, the widening of differences in urbanization levels and differences in financial support for agriculture, and the narrowing of differences in the educational attainment of rural labor have significantly contributed to the formation of provincial spatial linkages. This study reveals that China's government needs to give full play to the role of core regions as "leaders", and promote the balanced and coordinated regional development of low-carbon agriculture in China. In addition, policy makers should further optimize the spatial allocation of agricultural resource elements between provinces. The findings of the study provide reference suggestions for the development of regionally differentiated agricultural low-carbon development plans.

KEYWORDS

agriculture, low-carbon total factor productivity, spatially linked networks, social network analysis, super-efficiency ray slacks-based model

1 Introduction

In recent years, the problem of excessive carbon emissions has attracted the attention of the global public, governments, and academia. To reduce carbon emissions, countries are actively taking measures (Yu and Wu, 2018; Zhao et al., 2018). China is currently the largest carbon-emitting country in the world, and the Chinese government has committed to reaching peak carbon emissions around 2030, enacting a series of laws and regulations to break down energy conservation and emission reduction in various regions and industries (Zhou et al., 2020; Yang et al., 2022a).

Agriculture is one of the core sectors in a country to ensure the security of food supply and maintain socioeconomic stability, and its sustainable development is closely related to people's welfare. China's total agricultural output value of 139.7 billion RMB increasing to 147013.40 billion RMB in 2021. However, the tremendous achievement has been accompanied by a transition in resource consumption and a surge in agricultural carbon emissions (Xu and Lin, 2017; Zhang L. et al., 2019). Agricultural carbon emissions account for about one-fifth of China's total carbon emissions (Guan et al., 2008; Liu et al., 2021), as the second largest source of carbon emissions in China, agricultural production activities generate 50% of CH_4, 70% of N_2O and 28.5% of CO_2 (Zhang X. et al., 2019; Yue et al., 2021). Hence, low carbon agricultural development for China and emerging economies like China means adopting a low carbon emission development model while maintaining total economic output and low carbon emissions (Ang and Su, 2016; Wu J. et al., 2020; Hamid and Wang, 2022).

The impact of China's agroecology deserves high priority (Li and Wu, 2022; Wu et al., 2022). The relevant documents guiding the work of "agriculture, the countryside and farmers" further emphasize the promotion of green transformation of agriculture in 2022. With the development of agricultural mechanization and agricultural intensification, China's agricultural production activities have become increasingly dependent on the use of chemical materials such as fertilizers, pesticides, and plastic films (Zhen et al., 2017), which are important sources of excessive CO_2 emissions (Wang L. et al., 2022). In addition, advances in farming technology and increased demand for meat have led to a significant increase in CH_4 and N_2O emissions from livestock (Qian et al., 2018). In previous studies, the environmental and social impacts of livestock production patterns have been largely ignored (Escribano et al., 2022). Therefore, integrated consideration of carbon emissions from farming and livestock is important for China to achieve sustainable agricultural development (Paul et al., 2019). This paper examines agricultural carbon emissions based on the broad scope of agriculture. It refers to the greenhouse gas emissions directly or indirectly caused by the agricultural production process, including carbon emissions caused by agricultural land use activities such as fertilizers, pesticides, and CH_4 and N_2O from enteric fermentation and manure management in livestock.

Uneven regional development is a challenge for many developing countries, and the gap between backward and developed regions is not only an economic issue but also a source of social conflicts. The practice of poverty reduction in China proves that it is particularly important to focus on coordinated regional development. With the improvement of the national market mechanism and the free flow of factors across regions, the spatial connection between regions is getting closer and closer, the process of regional economic integration is advancing (Hao et al., 2021), and the exchange and cooperation of agricultural development between regions are no longer limited to neighboring areas, but presents the characteristics of a complex network, and there is a spatial interaction effect of agricultural carbon emissions between regions (Cui et al., 2021; Liu and Yang, 2021; Wu et al., 2021). In reality, there is extensive communication among farmers, and contacts between farmers or rural neighbors are the main channel to obtain agricultural technology information (Tze Ling et al., 2011; Genius et al., 2014). Social networks promote green technology diffusion by enhancing communication among farmers and are an effective way for agricultural technology to spread (Li et al., 2017; Cai et al., 2022). Agriculture has strong positive inter-regional spillover effects, so expanding inter-regional cooperation in agricultural research can increase efficiency, and in particular, training researchers in less productive areas can increase TFP (Zhan et al., 2017).

The contributions of this study are threefold. First, we incorporate both carbon emissions from farming and livestock into the research framework of green agricultural development and use them as non-expected outputs to accurately examine the spatial network characteristics of low-carbon agricultural development in China and its evolutionary trends. Second, we adopt an alternative research idea different from linear causality analysis-social network analysis, focusing on the two-way interaction between research objects, breaking the gap between micro and macro, and eliminating all kinds of dichotomous problems. The roles and functions of each region in the spatial network structure of agricultural low-carbon development were further screened. It provides a reference basis for promoting the balance and coordination of regional low-carbon development. Third, we further explore the influence of the spatially linked network characteristics of regions on their green development and analyzed the drivers of network formation, we find space for the development of green agriculture in China. As a result, this study examines the inter-regional interactions, aiming to further promote inter-regional spatial linkages and achieve inter-regional complementarities and coordinated development. It not only provides referenceable suggestions to promote the formation of China's agricultural carbon reduction policy and the construction of a cross-regional green synergistic governance mechanism but also provides experience value to the economic transformation and stable development of other emerging real economies like China.

The rest of the paper is described as follows: Section 2 composes the relevant literature on research progress, and Section 3 includes the methodology and data sources used. In Section 4, we present the main findings and some brief discussions, and Section 5 provides an empirical analysis of the relevant network drivers. In Section 6, we provide the conclusions and policy implications of the study.

2 Literature review

Accurate analysis of ALTFP growth is crucial for designing policies to obtain their effectiveness (Shen et al., 2019), especially for one of the world's largest food producers and food consumers like China, where production efficiency that takes into account environmental factors is important for achieving sustainable agricultural development (Dakpo et al., 2016; Wang et al., 2018; Liu et al., 2022). In terms of calculation methods for agricultural TFP, most scholars use data envelopment analysis (DEA) (Gong, 2020) and stochastic Frontier analysis (SFA) approaches (Zhang L. et al., 2019). Environmental factors were not considered in earlier studies (Suhariyanto and Thirtle, 2001; Bai et al., 2012). With the increasing environmental constraints in agricultural production, scholars have started to work on agricultural green TFP that takes environmental factors into account (Zhong et al., 2021). In subsequent empirical studies, scholars have identified some limitations of the traditional ML index (Battese et al., 2004); A global measurement technique index that uses all measurement periods as a benchmark for the efficiency Frontier surface was proposed (Pastor and Lovell, 2005; Fukuyama and Weber, 2009). The global measurement technique and the ML measurement technique were combined based on Pastor and Lovell to form the Global Malmquist-Luenberger (GML) index (Oh, 2010), it is gradually used by Frontier researchers in this field (Ren et al., 2022). Compared with the traditional ML index, the GML index can effectively solve the problem of linear programming without feasible solutions. The research process considers group heterogeneity, divides the sample into several groups, and introduces the concept of common Frontier and group Frontier, which is more suitable for regional variance analysis (O'Donnell et al., 2008). In this paper, the Super-efficiency ray slacks-based measure (Super-RSBM) model and the GML index were chosen for further calculations.

At present, research on the assessment of the low carbon development level of Chinese agriculture and its influencing factors has yielded fruitful results. Cheng et al. (2016) and Qin et al. (2022) studied from the perspective of single-factor productivity, and examined the agricultural carbon productivity of 31 provinces and regions in mainland China during the period 1997–2012. Ji and Xia (2020), Guo and Liu (2021) analyzed the spatial and temporal convergence of agricultural green TFP in China from a dynamic perspective. Yang et al. (2019) explored the degree of spatial divergence of agricultural green TFP. The main influencing factors of low carbon development in agriculture are crop insurance (Carter et al., 2016; Fang et al., 2021), digital inclusive finance (Gao et al., 2022), agricultural financial subsidies (Li et al., 2021), industrial agglomeration (Wu J. et al., 2020), farmers' characteristics, economic development level, farmers' income level, financial support to agriculture (Adnan et al., 2018), agricultural structure, resource utilization, and environmental pollution control level (Liu et al., 2021), the foreign trade of agricultural products, and foreign direct investment in agriculture and agricultural technology input (Chen Y. et al., 2022), all of which showed that the agricultural green development in China showed a good trend, but the inter-provincial differences widened, and the spatial distribution gradually became uneven, with significant spatial dependence. Hence, it is necessary to pay attention to the spatial interaction effect between regions and gradually reduce the regional disparity in agricultural development (Li et al., 2019).

In the study of spatial linkage in carbon emissions, a portion of scholars has used spatial measures. Spatial measurement only considers the influence of "quantity", but not the influence of "relationship". The social network approach can overcome the shortcomings of the spatial measurement approach and is increasingly used in the spatial relationship of carbon emissions. For example, He et al. (2020) constructed a spatially correlated network of carbon emissions from the power sector in each province of China, Bai et al. (2020) examined the structure of the spatially correlated network of carbon emissions from transportation in China and its drivers, Liu and Xiao (2021) studied the spatial correlation of carbon emissions from industry in China, Huo et al. (2022) and Wang Z. et al. (2022) examined the spatially correlated network structure of carbon emissions from buildings in China network structure and its drivers, and Song et al. (2019) explored the spatial structure pattern and correlation effects of carbon emissions in the Chengdu-Chongqing urban agglomeration. However, few studies have applied social network analysis methods to carbon emission relationships in agriculture.

The current research on low-carbon development in agriculture has achieved richer results, but there is still room for further improvement and supplementation. First, in the measurement of ALTFP, most studies have taken farming as the main object and selected six aspects of agricultural production: fertilizer, pesticide, agricultural film, tillage, machinery use, and irrigation as carbon sources to measure agricultural carbon emissions. However, the fact that farming and livestock have long each accounted for half of China's total agricultural carbon emissions, so carbon emissions from livestock should also be taken seriously. Second, the spatial linkage of ALTFP is mostly based on "attribute data", which results in local relationships, and the variables need to satisfy the assumption of independent interconnectedness. Third, many research results empirically proved the existence of spatial linkages in low-carbon agricultural development in China but did not further clarify the reasons for the formation of spatial linkages. Therefore, the study firstly measured China's ALTFP from 2001 to 2020 with the Super-RSB model from the perspective of farming and livestock. Secondly, drawing on the modified gravity model, the spatially linked network structure of green agricultural development in different provinces was analyzed using social network analysis. Finally, using the Quadratic Assignment Procedure (QAP) to explore the driving factors of low-carbon development in agriculture, and analyze the reasons that led to the unbalanced development of regional low-carbon agriculture.

3 Methodology and data allocation

3.1 Calculation of ALTFP

Green/low carbon total factor productivity has become an important basis for judging the sustainability of the economy[1](Liu et al., 2021; Hao et al., 2022). While earlier DEA models could measure environmental efficiency with undesired outputs, the weak disposable relationship that exists between undesired and desired outputs was ignored. The introduction of a DEA model with a directional distance function partially corrects this deficiency. However, the designation of direction vectors is subjective, the improvement of each decision-making unit (DMU) may not be unique, and these models do not take into account the weak disposable relationship between desired and undesired outputs, to solve this problem, Song et al. (2018) introduced polarity theory into the SBM model and proposed the RSBM model. In this paper, RGML index is used to measure ALTFP, which was measured by referring to Song et al. (2018). The constructed Super-RSBM model is:

$$\delta_o^* = \min \delta_o = \frac{1 + \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{io}}}{1 - \frac{1}{s+1}\left(\sum_{r=1}^{s}\frac{s_r^+}{y_{ro}} + \frac{s_{\|z\|}^-}{z_o}\right)}$$

$$\begin{aligned} \text{s.t.} \sum_{j=1, j\neq 0}^{n} \lambda_j x_{ij} + s_i^- &\le x_{io}, i = 1, 2, \ldots, m \\ \sum_{j=1, j\neq 0}^{n} \lambda_j y_{ij} - s_r^+ &\ge y_{ro}, r = 1, 2, \ldots, s \\ \sum_{j=1, j\neq 0}^{n} \lambda_j \|z_j\| - s_{\|z\|}^- &\le z_o \\ 1 - \frac{1}{s+1}\left(\sum_{r=1}^{s}\frac{s_r^+}{y_{ro}} + \frac{s_{\|z\|}^-}{z_o}\right) &> 0 \\ \lambda_j, s_i^-, s_r^=, s_{\|z\|}^- \ge 0, j &= 1, 2, \ldots, n \end{aligned} \tag{1}$$

Where $s_i^-, s_r^+, s_{\|z\|}^-$ represent the slack in inputs, desired, and undesired outputs. In slack variables, the objective function is monotonically decreasing. For the effective DMU_O to be evaluated, the DEA unit is effective only when $\delta_o^* \ge 1$, while the higher the value δ_o^* the higher the efficiency.

The above equation can calculate the efficiency value of the evaluated unit under certain technical conditions, but technical efficiency at this point is a static analysis that cannot reflect the direct impact of productivity changes on agricultural production and development. For this reason, the GML index is introduced. Compared with the ML index, the GML index can effectively solve the problem of linear programming without feasible solutions. Referring to (Oh, 2010), the RGML index is defined as follows:

$$RGML^{t,t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}; x^t, y^t, b^t\right) = \frac{1 + D_G^T\left(x^t, y^t, b^t\right)}{1 + D_G^T\left(x^{t+1}, y^{t+1}, b^{t+1}\right)} \tag{2}$$

If $RGML^{t,t+1}<1$, then desired output decreases and non-desired output increases, and ALTFP is lower than the previous period level, conversely, the ALTFP is higher than the previous period level. When $Rgml^{t,t+1}$ taking the non-negative value and its value is greater than 1, it indicates that ALTFP increases. Considering that Malmquist is a chain index, which is a dynamic growth rate, this paper transforms ALTFP into a fixed base index to reflect the cumulative trend of ALTFP. $ALTFP_{2001} = ALTFP_{2000} \times Mal_{2001}$, The ALTFP in 2000 is 1 and Mal_{2001} is the Malmquist index in 2001. By analogy with this formula, we can obtain the TFP values for all years, with 2000 as the base period and excluded in the empirical test summary.

3.2 Determination of spatial correlation of ALTFP

Determining the spatial linkages of ALTFP is the key to effective analysis, and this paper draws on an improved trade gravity model to determine. Provinces are the points in the association network, and inter-regional linkage relationships are the lines in the network, thus constituting the spatial network of regional development. According to the existing literature, most scholars generally use vector autoregressive (VAR) models, gravity models, and Moran's I index to determine spatial relationships. However, the VAR model is deficient in providing reasonable economic theoretical explanations, it cannot reflect the simultaneous relationships between variables or portray the evolutionary trends of spatial structures, and it is too sensitive to the choice of lag order, which can seriously degrade the network structure characteristics (Lui et al., 2007). Gravity models can integrate relevant economic geographic factors and reveal the evolutionary characteristics of

1 In this paper, we mainly measure agricultural green/low carbon total factor productivity with agricultural carbon emissions as non-expected output, which is also the currently adopted method, and all will appear in the paper as agricultural low carbon TFP for conceptual clarity.

spatially linked relationships in time series and cross-sections. In our study, the gravity model was introduced into the field of agricultural green development concerning (Chen Z. et al., 2022). To improve the applicability of the model, the model was modified as in Eq. 3:

$$G_{ij} = k_{ij}\frac{\mathrm{ALTFAPLTFP_j}}{\left[D_{ij}/\left(g_i - g_j\right)\right]^2},\ k_{ij} = \frac{\mathrm{ALTFP_i}}{\mathrm{ALTFP_i + ALTFP_j}} \tag{3}$$

Where G_{ij} denotes the association strength of ALTFP in provinces i and j. $ALTFP_i$ is the ALTFP for province i, D_{ij} is the geographical distance expressed as the spherical distance between the capital cities of province i and province j. $(g_i - g_j)$ is the economic distance expressed in terms of the GDP per capita of the two provinces. k_{ij} is the gravitational constant, usually take 1. However, considering the inter-provincial differences in resource endowments and development approaches. There is a two-way and non-reciprocal spatial correlation in ALTFP, so we use the proportion of ALTFP to correct k_{ij}.

The spatial correlation matrix of inter-provincial ALTFP is obtained from the modified gravity model, and the average value of each row of the gravity matrix is taken as the threshold value. When greater than the threshold than 1, it indicates a correlation between the provinces in each row and the provinces in this column for ALTFP; otherwise, it takes 0, which means there is no correlation between this row and the provinces in this column.

3.3 Social network analysis

With the gradual deepening of regional coordination strategy and the enhancement of the mobility of market factors, the spatial correlation effect of the regional economy is becoming more and more significant, and there are complex economic links between regions. The same is true of the agricultural economy. Spatially linked networks of low-carbon economies in agriculture are an important part of the economic network, its inner mechanism of formation is a network organization system combining points, lines, and surfaces of capital, resources, labor, low-carbon technologies, and management methods under the guidance of the concept of low-carbon development and the role of several mechanisms, such as factor gathering and dispersal, market regulation, government control, and circular feedback.

Specifically, due to the spatial heterogeneity of geographical location, factor endowments, agricultural development patterns, and agricultural low-carbon technologies in each region, the agricultural economy does not develop in a balanced manner, which leads to a certain "potential energy difference" in the development of agricultural low-carbon economy in each region, providing a "source of power" for the flow of various factors between regions. In this process, the market regulation mechanism guides the flow of agricultural low-carbon development factors to regions with high marginal benefits through supply and demand and prices, forming the core and peripheral areas of a low-carbon economy. The government's macro-control mechanism is mainly through financial transfer payments, a performance appraisal system, and a regional coordinated development strategy to guide the "reverse gradient" flow of factors, promote regional advantages to complement each other, and achieve balanced and coordinated regional development (Yang et al., 2022b). Therefore, the factors of agricultural low-carbon development are constantly flowing and reconfiguring in space with human, logistics, and information technology flows as carriers, conducting and radiating to neighboring and other regions, it forms a complex spatially linked network of inter-regional agricultural low-carbon economic development. At the same time, under the role of the circular feedback mechanism, the low-carbon economy linkage network will also have an impact on the efficiency of agricultural green development in each region and the "potential energy difference" of inter-regional factor flow, which will eventually promote the accumulation of low-carbon agricultural economy cycle and gradual evolution.

The social network approach is unique in that the unit of analysis is not primarily the actors (e.g., individuals, groups, organizations, etc.), but rather the relationships between the actors. From the "relational" point of view, the object of study can be behavioral, political, social, and economic structures, so this approach is widely used in different fields. The RGML spatially relevant metrics in this paper are relational data, since relational data do not satisfy the "assumption of independence of variables" in the conventional statistical sense, multivariate statistical methods in the general sense do not apply to the analysis of relational data. Social network analysis was used to analyze overall network characteristics, regional network characteristics, and individual network characteristics, and the influence of network structure was tested empirically.

3.3.1 Whole network characteristics

Assessing the whole network characteristics of the spatial association network of ALTFP in Chinese agriculture using network density (D), network connectedness (C), network efficiency (E), and network hierarchy (H). Among them, D reflects the closeness of the connections between individuals in the network. The greater the network density, the greater the network's influence on the individuals. C reflects the robustness of the network, mainly measuring the reachability of each node, and if C is equal to 1, the network is robust. E reflects the number of redundant lines in the spatial network, the lower the network efficiency, the more stable the network. H reflects the position of each region in the spatial network, and the higher it is, the higher the position of a region in the ALTFP spatial association network. The calculation of network density

(D), network connectedness (C), network efficiency (E), and network hierarchy (H) is as presented in Eq. 4:

$$\begin{aligned} D &= \frac{M}{[N \times (N-1)]} \\ C &= 1 - \left[\frac{V}{N(N-1)/2}\right] \\ E &= 1 - \frac{L}{\max(L)} \\ H &= 1 - \frac{K}{\max(K)} \end{aligned} \tag{4}$$

M is the number of relations existing in the network, N is the total number of network nodes, V is the number of unreachable point pairs in the network, L is the number of redundant lines in the network, and K is the logarithm of symmetric reachable points.

3.3.2 Regional network characteristics

The E-I distribution index is used to analysis of regional development differences of ALTFP spatial association network in Chinese agriculture, it is equal to the ratio of subgroup density to overall density, so the index takes a threshold value in the interval [−1, +1]. The closer the index is to 1, the closer the district subgroups are to each other (external relations) and the less factional forestry. The closer the index is to -1, the less inter-subgroup (external relationships) and the more relationships tend to occur between subgroups, implying a greater degree of factionalism. The closer the index is to 0, the more the number of relationships inside and outside the subgroups is similar, and the relationships tend to be randomly distributed, making it impossible to distinguish between subgroups. The formula for measuring the E-I distribution index is as follows:

$$E - I = \frac{EL - IL}{EL + IL} \tag{5}$$

EL represents the number of relationships between subgroups and IL represents the number of relationships between subgroups within。

3.3.3 Individual network characteristics

The degree-centrality (Dc), betweenness-centrality (Bc), and closeness-centrality (Cc) are used to analyze the individual network characteristics. Whereas, the degree-centrality reflects the local centrality index of the research subject, and measures the ability of individuals in the network to connect themselves to other individuals, without considering whether they can control others. In a directed network, the degree of each point can be divided into out-degree centrality (Oc) and in-degree centrality (Ic). The in-degree centrality indicates the extent to which the province is influenced by others, the out-degree centrality indicates the ability of the province to influence other provinces, and if the in-degree is greater than the out-degree, it shows a net benefit effect, and *vice versa*. Is a net spillover effect. Bc measures the actor's control over resources, in other words, a point is said to have a high Bc if it is on a shortcut to multiple other pairs of points, indicating that this point plays an important mediating role, and is therefore an index of control. Cc is a measure of control by others, if the "distance" between a point in the network and other points " are short, then the point is said to have a high Cc and is stronger in terms of its ability to transmit information. The expressions of degree-centrality (Dc), betweenness-centrality (Bc) and closeness-centrality (Cc) are respectively as follows:

$$\begin{aligned} Dc &= (Ic + Oc)/(2n-2) \\ Bc &= \sum_{j}^{n}\sum_{k}^{n}\frac{g_{jk}(i)}{g_{jk}}, j \neq k \neq ij < k \\ Cc &= \sum_{j=1}^{n} d_{ij} \end{aligned} \tag{6}$$

n is the total number of network nodes, g_{jk} is the number of shortcuts that exist between point j and point k, $g_{jk}(i)$ is the number of shortcuts that exist between point j and point k through the third point i, d_{ij} is the distance of the shortcut between point i and point j (the number of lines contained in the shortcut).

3.3.4 The analysis of QAP

To investigate the influencing factors of Chinese ALTFP spatial association networks with the help of the Quadratic Assignment Procedure. Agricultural carbon emissions and subject to multiple and complex factors, the correlation between independent variables is a key issue affecting the reliability of regression results. QAP is based on the permutation of matrix data, and the similarity analysis of each element in the two matrices is performed to obtain the similarity coefficients, while the coefficients are tested nonparametrically. It does not require the assumption of mutual independence between explanatory variables, thus it can well deal with the endogeneity of relational data. It mainly includes QAP correlation analysis and QAP regression analysis.

In performing QAP correlation analysis, QAP first permutes the rows and columns of a matrix simultaneously and then calculates the correlation coefficient between the permuted matrix and the other matrix, which guarantees that the independent and dependent variable matrices have interdependence in rows and columns, and then calculates the significance and the probability that the magnitude of the correlation coefficient is either smaller or smaller than the actual coefficient. In the QAP regression analysis, the first step is to perform a conventional multiple regression estimation for the long vector elements corresponding to the independent and dependent variable matrices, and the second

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TABLE 1 Description of agricultural production input and output variables.

Classification of indicators		Carve metrics	Indicator description
Input Indicators		Labor	Number of people working in agriculture, forestry, livestock and fishery
		Capital	Capital stock of agriculture, forestry and fisheries
		Machinery	Total power of agricultural machinery
		Land	Crop sown area and aquaculture area
		Natural Resources	Irrigated area measures water inputs
Outputs Indicators	Desired output	Total agricultural output	Total output value of agriculture, forestry, livestock and fishery at constant prices in 2000
	Non-desired outputs	Agricultural carbon emissions	Carbon emissions from farming and livestock

part is to perform a random permutation of the rows and columns of the dependent variable matrix simultaneously, and then re-estimate and save the estimated coefficient values and R^2 values. The procedure is repeated several hundred times to obtain the standard error of the estimated statistic.

3.4 Panel quantile regression model

To further examine the evolutionary process of the change in the coefficient of influence of network structural characteristics on ALTFP, a fixed effects panel quantile regression is used with reference to (Powell, 2020). Five representative quartiles were estimated: 10%, 25%, 50%, 75%, and 90%.

$$Q_{RGML}(\tau|X) = \sigma + \varphi(\tau)X \tag{7}$$

where Q_{RGML} is the conditional quantile of τ for a given condition of X, X denotes all explanatory and control variables, and φ(τ) is the quantile regression coefficient.

3.5 Data allocation

3.5.1 ALTFP

The data description of input and output variables in the calculation of ALTFP is shown in Table 1.

Among them, the undesired outputs are mainly carbon emissions from farming and livestock, which is calculated by the following formula:

$$E_1 = \sum E_i = \sum T_i \times \delta_i \tag{8}$$

E_1 is the total carbon emissions from farming, E_i is the carbon emissions from all types of carbon sources, T_i is the amount of each type of carbon source, δ_i is the emission factor for each type of carbon source.

The sources of carbon emissions from livestock are mainly methane (CH_4) emissions from ruminant gastrointestinal fermentation and livestock manure management anoxia and nitrous oxide (N_2O) emissions from livestock manure collection, storage, and composting processes, calculated as:

$$E_2 = \sum GWP_{CH_4} \times D_i \times \delta_{1i} + \sum GWP_{CH_4} \times D_i \times \delta_{2i} + \sum GWP_{N_2O} \times D_i \times \delta_{3i} \tag{9}$$

E_2 is the total carbon emissions from livestock, GWP_{CH_4}, GWP_{N_2O} are the greenhouse benefit indices of CH_4 and N_2O, D_i is the average annual stocking of livestock, δ_{1i}, δ_{2i}, $\delta_{3i}$are emission factors for livestock gastrointestinal fermentation CH_4, manure fermentation CH_4 and N_2O. The carbon sources and emission factors for each type of carbon emission are shown in Table 2.

3.5.2 Data sources

The data were obtained from the public data of the China Statistical Yearbook, China Population and Employment Statistical Yearbook, China Agricultural Yearbook, China Rural Statistical Yearbook, China Agricultural Statistics, China Environmental Yearbook, and some provincial and municipal statistical yearbooks from 2001 to 2020. The geographical distances between provincial capitals were calculated with the help of ArcGIS10.8.

4 Results and discussions

4.1 Dynamic distribution of ALTFP in China

The RGML index of ALTFP was measured according to Eqs. 8, 9, and the probability distribution of the RGML index in different regions is plotted in Figure 1. Overall, the RGML index is highest in the east, followed by the west, and lowest in the northeast. In terms of the dispersion of values, there are more discrete values of high loci in the eastern region, while ALTFPs in other regions are not high and are more evenly distributed, especially the smallest and most concentrated

TABLE 2 Carbon sources, emission factors and sources of agricultural carbon emissions.

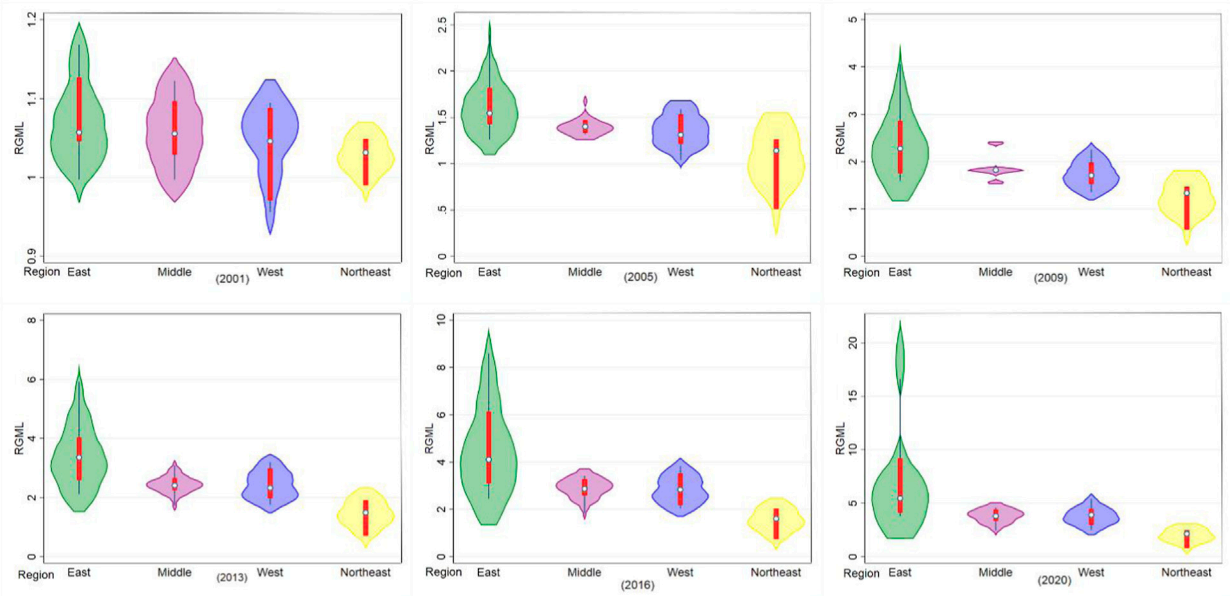
Carbon sources	Emission factors			Unit	References sources
Fertilizer	0.8956			Kg/Kg	Oak Ridge National Laboratory (2009)
Pesticides	4.9341			Kg/Kg	Oak Ridge National Laboratory (2009)
Agricultural film	5.1800			Kg/Kg	Agricultural Resources and Ecological Environment Institute, Nanjing Agricultural University
Diesel	0.5927			Kg/Kg	The Intergovernmental Panel on Climate Change (2006)
Plowing	3.1260			Kg/hm2	School of Biology and Technology, China Agricultural University
Irrigation	25.0000			Kg/Cha	Dubey (2009)
Carbon sources	Emission factors of CH_4		Emission factors of N_2O	Kg/head/year	All coefficients are from The Intergovernmental Panel on Climate Change (2006), where the CH_4 greenhouse efficiency index is taken as 25, and The N_2O greenhouse efficiency index was taken as 298
	Gastrointestinal fermentation	Fermentation of manure			
Pig	1.00	4.00	0.53	Kg/head/year	
Rabbit	0.25	0.08	0.02	Kg/head/year	
Poultry	0.00	0.02	0.02	Kg/head/year	
Dairy cattle	61.00	18.00	1.00	Kg/head/year	
Non-Dairy cattle	51.40	1.50	1.39	Kg/head/year	
Horse	18.00	1.64	1.39	Kg/head/year	
Donkey	10.00	0.90	1.39	Kg/head/year	
Mule	10.00	0.90	1.39	Kg/head/year	
Goat	5.00	0.17	0.33	Kg/head/year	
Sheep	5.00	0.15	0.33	Kg/head/year	
Camelot	46.00	1.92	1.39	Kg/head/year	

values in the northeastern region. In terms of temporal trends, ALTFP gradually increases over time, and in 2001, the RGML indices among the four major regions were all low but with small differences, and in 2005, the RGML indices in the central and western regions tended to converge, while the discrete values of the low loci in the northeast increased. Starting from 2015, the RGML index in the eastern region further increased, accompanied by an increase in the discrete values of the high points. In other regions, the increase of RGML index is smaller than that in the eastern region, but the dispersion value decreases, it indicates that the balanced development of the region has achieved some success.

Note: Violin diagram as a combination of box line diagram and kernel density diagram, The box line plot shows the location of the quantile, and the violin plot shows the density at any location. The white dots are the medians, the red box shapes range from the lower to upper quartiles, and the thin blue lines indicate whiskers. The external shape is the kernel density estimate.

4.2 Spatial association network characteristics and evolutionary trends

Inspired by Luo et al. (2021), we used ArcGIS to conduct a comparable analysis. Figure 2 visualizes the intensity of spatial association of provincial ALTFP in China in 2020. According to Eq. 6, considering the bidirectional and asymmetric nature of provincial ALTFP, if two provinces are connected by only one line, the difference in the magnitude of their bidirectional association cannot be reflected. Therefore, if the left graph in Figure 1 shows the gravitational intensity of province i to



Note: Violin diagram as a combination of box line diagram and kernel density diagram, The box line plot shows the location of the quantile, and the violin plot shows the density at any location. The white dots are the medians, the red box shapes range from the lower to upper quartiles, and the thin blue lines indicate whiskers. The external shape is the kernel density estimate.

FIGURE 1
Dynamic distribution of ALTFP from 2001 to 2020.

province j, the right graph shows the gravitational intensity of province j to province i.

In Figure 2, the spatial association network of ALTFP in China's province has broken the traditional geographical limitation of neighbor as friend, has a complex, multi-threaded spatial association network overflowing to non-neighboring provinces, showing a situation of "dense in the east and sparse in the west". From the gravitational strength of the line colors, the whole network forms a radiation network with Shanghai and Beijing as the south and north centers, and the association strength of Beijing-Tianjin-Hebei and Yangtze River Delta urban agglomeration is significantly higher than that of other regions.

Further, to analyze the spatial association network structure morphology of ALTFP, the spatial association intensity data obtained from Eq. 6 were binarized to turn the attribute-based data into relational data, and the spatial network topology of Chinese ALTFP in 2001 and 2020 was plotted using the visualization tool Net draw of UCINET (Figure 3). It can be seen that from 2001 to 2020, the density of the spatial association network of China's ALTFP has increased significantly, and the inter-regional connections have gradually become closer. Among them, Beijing, Shanghai, and Tianjin have been in the core position in the whole network, while most of the western provinces are at the edge of the network and have less connection with other provinces. Mainly because these regions have strong economic development capacity, strong capital, talent, and agricultural green innovation base, and have good transportation infrastructure and strong factor mobility. This greatly reduces the cost of green technology spillovers and thus forms the core region of the spatially linked network of agricultural green development.

4.2.1 The whole network characteristics

In terms of network density (Figure 4), network relevance and network density maintain the same evolutionary trend during the sample period, showing an "inverted U-shape" evolutionary trend that slopes first and then decreases. In terms of specific values, the number of network relationships was 150 in 2001, peaked at 187 in 2017, and dropped to 181 in 2020. Correspondingly, the overall network density increased from 0.17 in 2001 to 0.22 in 2015, and then decreased to 0.21 in 2020, it still has a large gap between the maximum number of possible network relationships (870) and the maximum possible network density 1, indicating that the spatial correlation of ALTFP is still at a low level and the linkage spillover effect between them is low.

In terms of network relevance, we adopt network connectedness, network efficiency, and network hierarchy to reflect the connectedness of the spatially connected network

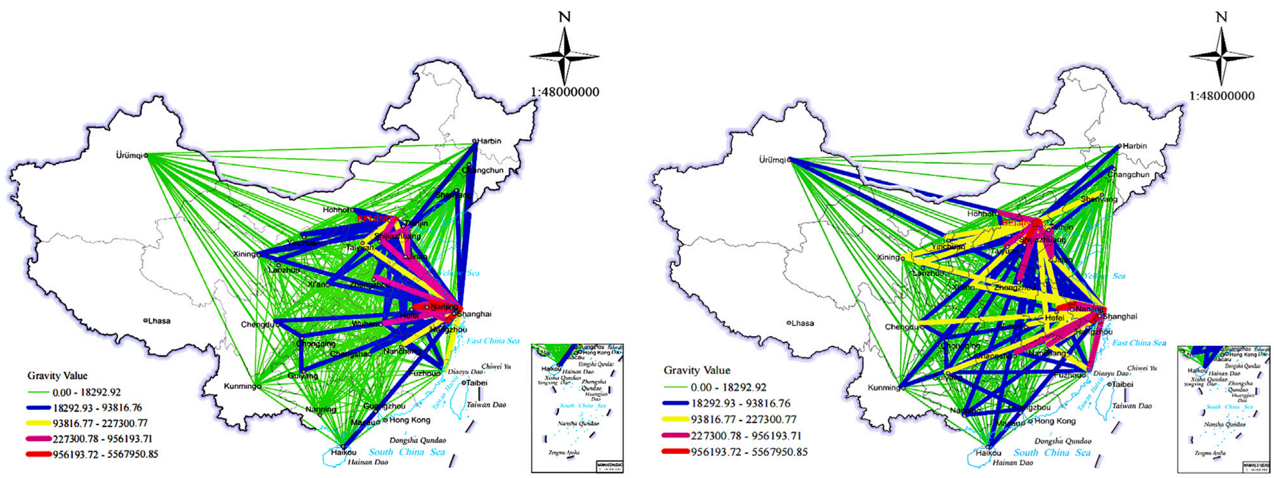


FIGURE 2
Spatial correlation intensity of ALTFP in China in 2020. Note: The map is made based on the standard map downloaded from the standard map service website of the National Bureau of Surveying, Mapping and Geographic Information, with the review number GS (2019) 1,673 and no modification of the base map (https://service.tianditu.gov.cn/#/).

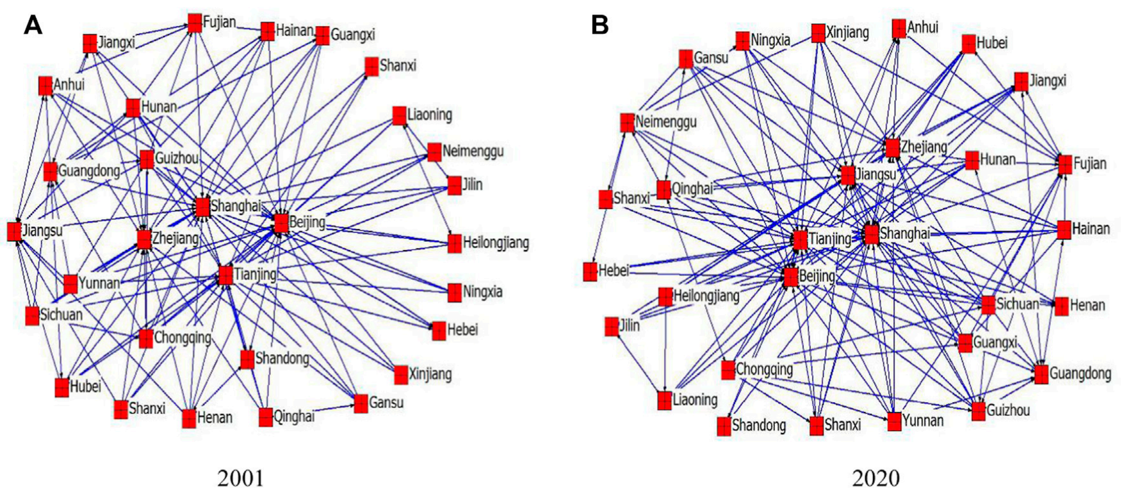


FIGURE 3
Structure of ALTFP in China in 2001 **(A)** and 2020 **(B)**.

structure of ALTFP in China (Figure 5). The network connectedness showed an obvious stepwise upward trend from 0.776 in 2001 to 0.871 in 2020, indicating that the connectivity and robustness of the network were gradually strengthened, and provinces could be spatially linked through direct and indirect means. In terms of network hierarchy, the value declined from 0.385 to 0.245 from 2001 to 2020, showing a stepwise decline, indicating that the hierarchy structure of Chinese ALTFP is gradually loosening, but there is still a hierarchy gradient and the network structure needs to be further optimized. In terms of network efficiency, the network efficiency declined from 0.783 in 2001 to 0.727 in 2020, with a less pronounced decline than the network hierarchy, indicating that although the connectivity of inter-provincial nodes is gradually increasing, there is still a high number of redundant relationship numbers, and there is an obvious phenomenon of overlapping association in the network of each province.

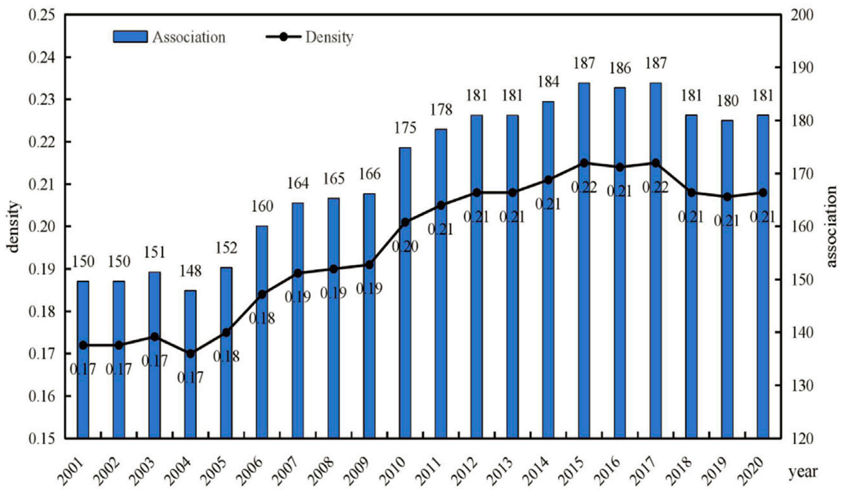


FIGURE 4
Network association and network density.

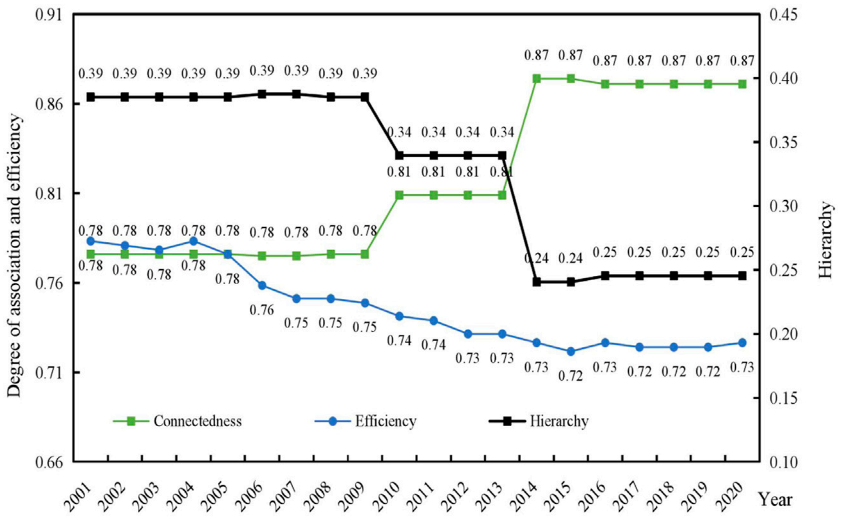


FIGURE 5
Network association, network efficiency, and network hierarchy.

4.2.2 Regional network structure characteristic

The study shows that there are significant differences in economic and social development between regions in China (Wu H. et al., 2020), and the regional differences in agricultural carbon emission rates mainly come from the regional differences between East-Central-West. To further investigate the spatial correlations of low-carbon agricultural development between regions, the 30 provinces in China were divided into four regions: eastern, central, northeastern, and western. The association network E-I index and the density matrix of each zone of the Chinese ALTFP were obtained by measuring the four major sectors as a unit.

The degree of faction throughout the network from 2001 to 2020 of ALTFP shows a narrowing trend (Figure 6). The E-I association index of the entire network of China's ALTFP was 0.543 in 2020, indicating that relationships tend to occur among the four major segments, with a smaller degree of factional forestry. In terms of regional density (Table 3), the

TABLE 3 Spatial correlation density matrix of ALTFP in four major regions of China in 2020.

Region	East	Middle	West	Northeast
East	0.40	0.55	0.56	0.40
Middle	0.55	0.00	0.02	0.00
West	0.56	0.02	0.22	0.00
Northeast	0.40	0.00	0.00	0.67

northeastern network has the highest density of 0.67, indicating that resources are more closely linked to agricultural development in the northeast. The density of 0.40 in the eastern region may be confined to the obvious natural resource-dependent attributes of agricultural development, the large north-south span, the different natural resource attributes, and the north-south policy differences, thus reducing the spatially linked network density of ALTFP in the eastern region. The density in the central and western regions is smaller, which may be limited by the regional economic development base and natural resource endowment differences.

In terms of inter-regional connections, the East is more strongly connected to the Midwest and generally connected to the Northeast. The Central region has strong connectivity with the East, little connectivity with the West, and almost no connectivity with the Northeast. The western region also has almost no connection with other regions except for the strong connection with the east. The northeast is only connected to the east. It is found that the four major regions are spatially connected, with the eastern region being more closely connected to other regions, while the central, western, and northeastern regions have very few connections with each other. Combined with the spatial linkage density of the regions themselves, the East is more connected both internally and externally, with the Northeast having a higher density value of its internal connections than that of its connections with other regions, indicating that the northeastern region has formed a “cohesive subgroup” locally. The central and western regions, on the other hand, are highly factionalized, with relatively few internal and external linkages.

4.2.3 Individual network structure characteristics

To further illustrate the position and role of each province in the spatially linked network of agricultural low-carbon development, we measured the centrality of each province. The results show that there are no significant changes in the indicators for each province during the sampling period; therefore, we analyzed the indicators for 2020 as an example, which are reported in Table 4.

First, degree centrality is used to discriminate whether each province is at the center of the ALTFP spatial network. The results show that six provinces are higher than the mean value of 32.18 of the degree-centrality, and all of these provinces are located in the economically developed areas of the eastern coastal region of China. Indicating that the eastern coastal region is more closely related to other provinces in the ALTFP network and is in the central dominant position in the spatially linked network of ALTFP. However, Anhui, Jilin, Liaoning, Shanxi, Xinjiang, Hubei, and Heilongjiang are in the last positions and are at the edge of the network. The in-degree is greater than the out-degree in 7 provinces, Beijing, Tianjin, Shanghai, Jiangsu, Zhejiang, Fujian and Anhui in 2020. It shows that these provinces benefit from the driving effect of ALTFP in other provinces, and their high level of agricultural low-carbon development can effectively attract resource elements of agricultural green development and transform them effectively to promote ALTFP, showing a significant spatial polarization effect.

Second, closeness-centrality was used to discriminate the ease of ALTFP spatial association generation among provinces. The mean value of closeness-centrality is 60.81, and the provinces that exceed the mean value and rank in the top five are Shanghai, Beijing, Tianjin, Jiangsu, and Zhejiang, indicating that these provinces have shorter distances from other provinces, and can quickly make connections with other provinces, and are central actors in the ALTFP spatial association network. This may be because these provinces are located in the eastern region with high inter-provincial resource mobility, and developed economic strength and accessibility expand access and capacity to agricultural development resources. In contrast, Xinjiang, Shanxi, Liaoning, Jilin, Anhui, Hebei, and Henan are ranked low, mainly because these provinces are mainly located in the geographical periphery of China and have weak links with other provinces, playing a marginal role in the linkage network.

Finally, the betweenness-centrality is used to reflect the ability of each province to control resources and information in the process of low-carbon development of agriculture. The mean value of betweenness-centrality is 2.42, with Shanghai, Tianjin, Beijing, Jiangsu, and Zhejiang exceeding the mean value. It shows that these provinces play the role of “intermediary” and “bridge” in the linkage network, have strong control and dominant role in the flow of talent, technology, and capital in low-carbon agricultural development, and are the important hubs in the linkage network. These provinces are located in the economically developed eastern region, with a high level of technological innovation and relatively high government regulation of extensiveness. It is easier to absorb the inflow of green development factor resources from other provinces and achieve strong control over other provinces. In contrast, Shanxi, Hubei, Xinjiang, Jilin, and Shanxi have lower betweenness-centrality and rank lower, indicating that these provinces are

TABLE 4 Centrality of spatially linked networks of ALTFP in China in 2020.

Provinces	Degree-centrality				Closeness-centrality		Betweenness-centrality	
	Out-degree	In-degree	Degree	No.	Degree	No.	Degree	No.
Beijing	7	23	79.310	3	82.857	3	13.003	3
Tianjing	6	24	82.759	2	85.294	2	14.862	2
Hebei	3	3	13.793	28	53.704	28	0.022	29
Shanxi	5	3	17.241	24	54.717	24	0.091	26
Neimenggu	6	6	31.034	7	59.184	7	0.732	7
Liaoning	4	2	17.241	25	54.717	25	0.071	27
Jilin	5	1	17.241	26	54.717	26	0.132	24
Heilongjiang	6	0	20.690	20	55.769	20	0.305	19
Shanghai	4	27	93.103	1	93.548	1	23.484	1
Jiangsu	5	19	65.517	4	74.359	4	7.514	4
Zhejiang	3	16	55.172	5	69.048	5	4.559	5
Anhui	4	5	17.241	27	54.717	27	0.126	25
Fujian	6	9	37.931	6	61.702	6	1.706	6
Jiangxi	7	5	24.138	16	56.863	16	0.359	16
Shandong	3	2	10.345	30	52.727	30	0.022	30
Henan	4	3	13.793	29	53.704	29	0.050	28
Hubei	6	2	20.690	21	55.769	21	0.196	20
Hunan	7	2	24.138	17	56.863	17	0.359	17
Guangdong	7	7	27.586	12	58.000	12	0.647	8
Guangxi	8	3	31.034	8	59.184	8	0.589	9
Hainan	8	1	27.586	13	58.000	13	0.359	18
Chongqing	9	5	31.034	9	59.184	9	0.545	10
Sichuan	9	1	31.034	10	59.184	10	0.528	11
Guizhou	8	4	31.034	11	59.184	11	0.528	12
Yunnan	8	2	27.586	14	58.000	14	0.528	13
Shanxi	5	2	20.690	22	55.769	22	0.170	23
Gansu	7	1	24.138	18	56.863	18	0.190	21
Qinghai	8	2	27.586	15	58.000	15	0.383	15
Ningxia	6	1	20.690	23	55.769	23	0.190	22
Xinjiang	7	0	24.138	19	56.863	19	0.410	14

in the marginal position of "dominated" in the correlation network.

4.3 Network structure effect analysis

Spatially linked networks are not only networks of relationships between regions, but also spatial flows and connections that contain knowledge and technology. The characteristics of the spatial network structure reflect the region's access to resources and the degree of connection with other regions, therefore, different characteristics of the network structure will affect the level of development of the region.

The indicators of overall network structural characteristics, regional network structural characteristics, and individual network structural characteristics were obtained using the previous calculations as explanatory variables, the agricultural low carbon TFP was selected as the explanatory variable for the sample survey period, and Ordinary Least Squares (OLS) was used to estimate. The explanatory and explanatory variables were treated using a logit strategy to avoid differences between indicators and multicollinearity. In addition, to examine the evolutionary process of the change in the impact effect of network structure, further fixed-effects panel quantile regressions were used to estimate representative five quartiles:10%, 25%, 50%, 75%, and 90%, as shown in Table 5. Among them, the estimation

TABLE 5 Results of the impact of the overall network structure on ALTFP.

Variables	Density					Connectedness				
	(1)OLS	(2)Q10	(3)Q25	(4)Q75	(5)Q90	(1)OLS	(2)Q10	(3)Q25	(4)Q75	(5)Q90
Whole network	5.045***	4.468***	4.479***	4.534***	6.288***	8.050***	7.904***	8.727***	8.216***	8.500***
	(0.540)	(0.330)	(0.421)	(1.260)	(0.917)	(0.908)	(0.833)	(1.350)	(1.240)	(0.978)
R^2	0.828	0.746	0.722	0.527	0.539	0.814	0.542	0.533	0.617	0.650
N	20	20	20	20	20	20	20	20	20	20
Variables	Hierarchy					Efficiency				
	(1)OLS	(2)Q10	(3)Q25	(4)Q75	(5)Q90	(1)OLS	(2)Q10	(3)Q25	(4)Q75	(5)Q90
Whole network	−2.008***	−1.999***	−1.783***	−2.027***	−2.189***	−0.147***	−0.124***	−0.129***	−0.135***	−0.157***
	(0.248)	(0.270)	(0.362)	(0.327)	(0.302)	(0.134)	(0.007)	(0.009)	(0.023)	(0.021)
R^2	0.785	0.514	0.450	0.592	0.617	0.863	0.785	0.765	0.585	0.538
N	20	20	20	20	20	20	20	20	20	20

Notes: ***, ** and * show the significance level at 1%, 5%, and 10%. The values in parentheses are standard errors. Same below.

results of the 50% quantile are only slightly different from the results of the other quantile in terms of coefficient magnitude, and the direction of the coefficient is consistent with the estimation results of the other quantile, so it is not shown in Table 5.

4.3.1 Impact of overall network structure on ALTFP

Table 5 reports the estimation results of the impact of overall network structure on ALTFP. Where model (1) is the result of OLS estimation and models (2) to (5) are the results of panel quantile estimation. It can be seen that the OLS estimated coefficients of network density, network connectedness, network hierarchy, and network efficiency are 5.045, 8.050, −2.008, and −0.147, all of which pass the 1% significance test, indicating that the overall network structure has a significant effect on the level of ALTFP. Increasing network density and network relevance, reducing network hierarchy and network efficiency can significantly improve the level of low carbon TFP in agriculture. The quantile regression estimation results showed that each indicator of network structure characteristics passed the 1% significance test at each quantile, and the signs were all consistent with the OLS estimation results, further indicating the reliability of the above results. This result is consistent with the findings of Qu and Huang (2021) and Chen Z. et al. (2022).

This may be because, firstly, the increase in network density indicates an increase in the number of associated relationships in the network, and the core provinces will exert a strong diffusion effect to drive the development of inter-provincial complementarities, ultimately promoting the growth of the ALTFP. Second, increased network connectivity can enhance the robustness and inter-regional connectivity of the network, all provinces can join the network, there is no isolated area, and the enhanced spatial spillover effect promotes the growth of ALTFP. Again, the reduction of network hierarchy can make the original one-way connected provinces develop into two-way connectivity, the advantageous provinces and the disadvantaged provinces gradually tend to be equal, and the provincial-led low-carbon TFP development model with the high level of economic development and rich agricultural science and technology resources changes to the overall agricultural green and coordinated development model, thus improving the overall agricultural green development level. Finally, the reduction of network efficiency has increased the connections in the relevant networks, that is, the network hierarchy has been reduced, thus reducing the factor endowment differences among provinces in agricultural low-carbon development, lowering the inter-provincial flow costs of agricultural low-carbon development factors, enhancing the relevance of regional resources to agricultural low-carbon development, and significantly improving the overall level of ALTFP.

4.3.2 Effect of regional network structure on ALTFP

The E-I index reflects the severity of regional assignment, and as shown in Table 6, regional network structure under OLS estimation significantly affects ALTFP at the 5% level with a coefficient of 0.380, indicating that the weakening of regional factional forestry is conducive to promoting agricultural low-carbon development. The quantile regression results show that the regional network structure can only play a role in the enhancement of ALTFP if the level of ALTFP is at the 75%.

TABLE 6 Results of the regional network structure influencing the effects.

Explained variables	ALTFP				
Estimation methods	(1)OLS	(2)Q10	(3)Q25	(4)Q75	(5)Q90
E-I index	0.380**	0.155	0.215	0.453*	0.139
	(0.147)	(0.267)	(0.292)	(0.226)	(0.221)
R^2	0.998	0.966	0.964	0.956	0.953
N	20	20	20	20	20

TABLE 7 Results for individual network structure effects.

Variables	(1)OLS	(2)Q10	(3)Q90	(1)OLS	(2)Q10	(3)Q90	(1)OLS	(2)Q10	(3)Q90
Degree-centrality	0.418***	0.179***	0.181***						
	(0.041)	(0.004)	(0.005)						
Closeness-centrality				4.734***	1.087***	1.088***			
				(0.776)	(0.057)	(0.045)			
Betweenness-centrality							0.129***	0.056***	0.055***
							(0.012)	(0.002)	0.002)
N	600	600	600	600	600	600	600	600	600

4.3.3 Effect of individual network structure on ALTFP

Model (1) in Table 7 is an OLS estimation using a panel data model, and models (2) to (3) are panel quantile regressions under the adaptive Monte Carlo method. Among them, the estimation results for the 25%, 50%, and 75% quantile points differ only slightly from those for the 10% and 90% quantile points in terms of the magnitude of the coefficients and are otherwise basically the same, so they are not shown in Table 7.

The OLS regression coefficients of degree-centrality, closeness-centrality, and betweenness-centrality are 0.418, 4.734, and 0.129, all of which are significant at the 1% significance level, indicating a significant positive effect of provincial centrality on increasing the level of ALTFP. This finding is consistent with that of Chen Z. et al. (2022).

Possible reasons are: firstly, the higher the centrality, the closer the relationship between a province and other provinces, and accordingly the higher the degree of local relevance, the more favorable it is that all provinces can benefit from the whole network structure and improve their ALTFP. Secondly, higher closeness-centrality means that the greater the sum of shortcut distances between a province and other provinces, the less likely the province's agricultural low-carbon development is constrained by other provinces, the closer the inter-provincial relationship, the higher the degree of inter-provincial communication and cooperation, the lower the cost of factor flow and resource allocation, and the increasing level of the province's agricultural low-carbon development. Finally, the provinces with higher betweenness-centrality have obvious comparative advantages in the ALTFP network, which can effectively guide the rational allocation of resource factors, effectively control the correlation effect with other provinces, and make the huge network structure regionally effective and reasonable, thus contributing to regional agricultural low-carbon development.

5 The analysis of driving factors about spatial differences of ALTFP

5.1 Analysis of driving factors of spatial association network of ALTFP

According to the mechanism analysis, the "potential energy difference" due to the difference between regions is the main driving force for the spatial closeness of the association of ALTFP. Next, the factors affecting the spatial association network are discussed, and the following nine relational variables are selected to examine the factors affecting the spatial association: 1) spatial proximity of Provincial adjacency (RO) is expressed as 1 if the two provinces are adjacent, otherwise it is 0. It has been confirmed that low carbon efficiency in agriculture between neighboring regions affects each other (Wu et al., 2015); 2) agricultural industry structure differences (ST) are expressed by the proportion of the output value of the farming in the total output value of agriculture, forestry, livestock, and fishery. Different crops differ in terms of resource consumption, marginal benefits, and carbon effects. Accordingly, the structure of farmland use determines the input mix, desirable output, and environmental burden. Therefore, the restructuring of farmland use may affect the flow and allocation of factors, which in turn affects agricultural low-carbon development generating spatial correlations (Zhu et al., 2019); 3) urbanization level differences (UR) are expressed by the proportion of the urban resident population to the total population. The essence of the urbanization process is a multidimensional transmutation process accompanied by the flow of capital, labor, technology, and other factors from the countryside to the city, and the reconfiguration of factors between urban and rural areas, which has a great impact on the production scale and cultivation structure of agriculture (Tian et al., 2016; Xiong et al., 2020; Joséf, 2022); 4) rural labor education level differences (ED) is expressed by the average years of education of rural residents. The labor force is the decision maker of agricultural production methods and its level of education has a significant impact on the adoption and application of pioneering technologies (Wang et al., 2019; Wu et al., 2021; Khanh and Nguyen, 2022); 5) financial development level differences (FI) is expressed by the ratio of deposit and loan balance of financial institutions to GDP, a sound financial service system can provide financial support for agricultural transformation and upgrading and green technology progress (Huang et al., 2014; Cao et al., 2022; Gao et al., 2022); 6) agricultural irrigation water utilization rate differences (WA) is expressed by the ratio of effective irrigated area to cultivated area in each region, agricultural irrigation water use efficiency can affect agricultural carbon emissions and output efficiency by changing inter-regional agricultural production costs and intra-agricultural production structure (Xu et al., 2022); 7) farmland operation scale differences (SC) is expressed by the per capita crop sown area, it has been proven that the scale of agricultural production leads to differences in the cost of adoption of agricultural technology, and that larger scale of operation makes it easier to obtain economies of scale and adopt advanced technology (Helfand and Taylor, 2021; Mao et al., 2021); 8) financial support differences (IN) is expressed by the proportion of local financial expenditure on agriculture, many scholars have found that financial support for agriculture significantly affects agricultural carbon emissions (Guo et al., 2022); 9) marketization level differences (MA) is expressed by the marketization index measurements, according to (Fan et al., 2011). The level of marketization determines the flow and allocation of production factors and therefore has an impact on the spatial association network (Guo et al., 2021). The model was constructed as follows:

$$R = f\,(RO, ST, UR, ED, FI, WA, SC, IN, MA) \tag{10}$$

Where R is the spatial correlation matrix of ALTFP after binarization, the rest of the indicator data are variance matrices consisting of the absolute differences in the mean values of the corresponding indicators for each province from 2001 to 2020. Figure 7 shows the results of the QAP analysis of the driving factors, it can be seen that there are different degrees of correlation between the drivers, implying that the impact of the driving factors on the spatial correlation network overlaps significantly and there is a high degree of multicollinearity among the driving factors, further indicating that the QAP regression analysis is more appropriate.

5.2 QAP correlation analysis

The correlation coefficients of each influencing factor with the structure of the spatial correlation network of low-carbon TFP in Chinese agriculture were first tested using the QAP method of the quadratic assignment procedure, as shown in Table 8. It can be seen that the correlation coefficients for province adjacency, differences in urbanization levels, differences in the education level of the rural labors, differences in financial development levels, and differences in agricultural irrigation water utilization rates are all significant, indicating that these influencing factors had a significant impact on the formation of the spatial correlation network. In contrast, the correlation coefficients of differences in agricultural industry structure, the scale of farmland operation, financial support to agriculture, and the level of marketization are not significant, indicating that their inter-provincial differences do not play a significant role in the spatial association structure of ALTFP.

5.3 QAP regression analysis

Using QAP regression to analyze the relationship between the spatial association network and the drivers, the results of regression fitting were obtained by 2000 random permutations (Table 8). The adjusted decision coefficient was 0.301, indicating that the drivers could explain about 30.10% of the variation in the structure of the spatial association.

The spatial proximity of provinces, differences in urbanization, differences in financial support for agriculture, differences in financial development levels, and differences in marketization have a positive effect on the formation of spatially linked networks. Among them: the coefficient of spatial proximity is significantly positive, which indicates that inter-provincial geographical proximity can break down the barriers to resource flow and promote

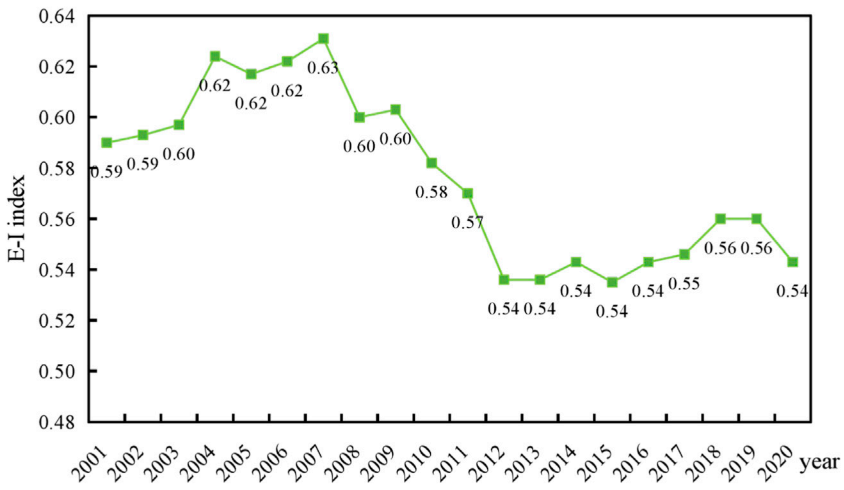
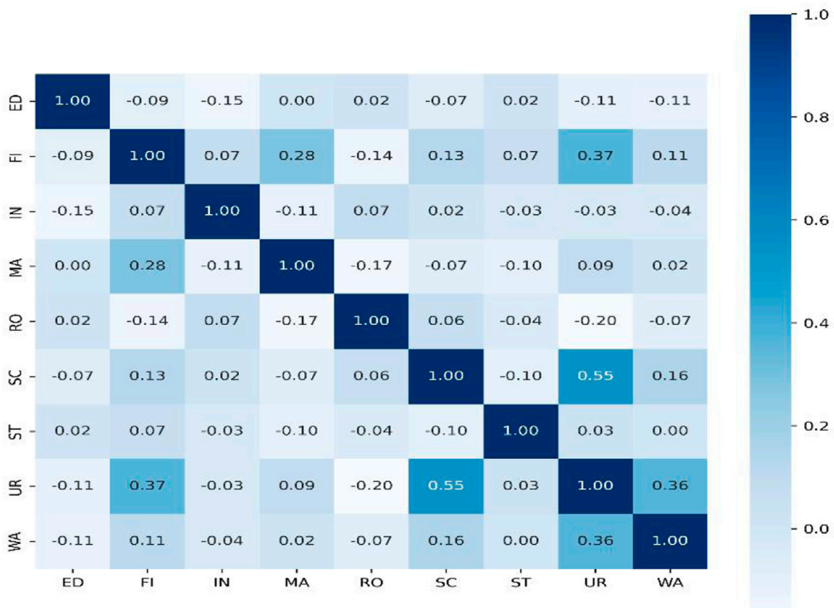


FIGURE 6
The trend of the E-I index of ALTFP in China from 2001 to 2020.



	ED	FI	IN	MA	RO	SC	ST	UR	WA
ED	1.00	-0.09	-0.15	0.00	0.02	-0.07	0.02	-0.11	-0.11
FI	-0.09	1.00	0.07	0.28	-0.14	0.13	0.07	0.37	0.11
IN	-0.15	0.07	1.00	-0.11	0.07	0.02	-0.03	-0.03	-0.04
MA	0.00	0.28	-0.11	1.00	-0.17	-0.07	-0.10	0.09	0.02
RO	0.02	-0.14	0.07	-0.17	1.00	0.06	-0.04	-0.20	-0.07
SC	-0.07	0.13	0.02	-0.07	0.06	1.00	-0.10	0.55	0.16
ST	0.02	0.07	-0.03	-0.10	-0.04	-0.10	1.00	0.03	0.00
UR	-0.11	0.37	-0.03	0.09	-0.20	0.55	0.03	1.00	0.36
WA	-0.11	0.11	-0.04	0.02	-0.07	0.16	0.00	0.36	1.00

FIGURE 7
Heat map of correlation coefficients of driving factors.

provincial mobility for low-carbon agricultural development. The specific reason may be the geographical proximity of the location with many similar characteristics, such as geographical environment, resource endowment, cultivation structure, and technology level, etc. These similarities reduce the cost of production factor flow and low-carbon technology diffusion and promote closer inter-regional linkages. The coefficient of urbanization differences is significantly positive, which indicates that provinces with greater urbanization differences are more likely to have economic linkages between regions, probably mainly because of the difference in urbanization levels, with

TABLE 8 The analysis of driving factors of spatial association network of ALTFP.

Variables	QAP correlation analysis				QAP regression analysis			
	Correlation coefficient	p-value	$p \geq 0$	$p < 0$	Regression coefficient	p-value	PA	PB
RO	0.127	0.001	0.001	0.999	0.180	0.000	0.000	1.000
ST	−0.067	0.140	0.860	0.140	−0.233	0.176	0.825	0.176
UR	0.467	0.000	0.000	1.000	0.018	0.057	0.000	1.000
ED	−0.013	0.014	0.987	0.014	−0.138	0.001	1.000	0.001
FI	0.239	0.003	0.003	0.997	0.012	0.402	0.402	0.599
WA	0.123	0.063	0.063	0.937	−0.124	0.419	0.581	0.419
SC	−0.063	0.176	0.724	0.176	−0.022	0.235	0.766	0.235
IN	0.084	0.124	0.124	0.876	1.397	0.086	0.086	0.915
MA	−0.031	0.326	0.675	0.326	0.003	0.435	0.435	0.566

Notes: PA, represents the probability that the regression coefficient from random substitution is not smaller than the observed regression coefficient in the two-tailed test, and PB, represents the probability that the regression coefficient from random substitution is not larger than the observed regression coefficient.

factors such as labor and capital tending to flow more from provinces with low levels of urbanization to those with high levels of urbanization, in the process promoting the spread of technological progress and radiation to neighboring regions. The coefficient of the difference in fiscal support to agriculture is significantly positive, which indicates that the greater the difference in the level of fiscal support to agriculture between provinces, the more likely it is to cause spatial correlation, mainly because finance provides the foundation for agricultural production, infrastructure, and advanced technology, the higher the level of financial support for agriculture in a province, the more it helps the region to establish a model for low-carbon agricultural development, attracting regions that are lagging behind in development to learn from and exchange with these regions, and promoting policy references and the diffusion and application of low-carbon technologies among provinces. And the regression coefficients of differences in the level of financial development and differences in the level of marketization are not significant ($p > 0.1$), indicating that inter-provincial differences do not yet significantly affect the formation of ALTFP spatial association networks in China.

Differences in the education level of rural labor, differences in irrigation water use efficiency in agriculture, differences in agricultural industry structure, and differences in agricultural production scale have negative effects on the formation of spatial association networks. Among them: the coefficient of influence of the difference in the education level of the rural labor is significantly negative, which indicates that the greater the difference in the education level of the regional rural labor force, the fewer its agricultural economic linkages, this is mainly because agricultural human capital largely affects the application of advanced agricultural technologies, and if the difference in human capital between regions is too large, it is not conducive to the absorption and digestion of technological overflows from advanced regions by regions with relatively low technology levels and will hinder the spread of advanced agricultural production technologies, thus not conducive to the formation of ALTFP spatially linked networks. Regression coefficients for differences in agricultural irrigation water use efficiency, differences in agricultural industry structure, and differences in agricultural production scale are not significant ($p > 0.1$), indicating that inter-provincial differences do not yet significantly affect the formation of ALTFP spatial association networks in China.

Agricultural irrigation water use efficiency reflects resource endowment. Generally speaking, the greater the difference in resource endowment, the stronger the complementarity between regions, and the more frequent the flow of logistics, capital, and technology with resource flow as the carrier, the more conducive to the formation and development of a spatially linked network of green economic efficiency. However, the results of this paper show that the effect of differences in agricultural irrigation water use efficiency on the spatial linkage network is not significant, probably because the role of resource endowment differences on the spatial linkage of green economic efficiency has been reduced in recent years as the development approach has shifted from factor-driven to innovation-driven, and technology substitution effects have become prominent. The main reasons for the insignificant effect of agro-industrial structure and marketization on the association network are: Due to the sticky nature of agricultural production and the inherent characteristics of agriculture such as strong dependence on natural resources and environmental endowments and weak risk resistance, the internal industrial structure of agriculture is more stable, resulting in the slow development of agricultural factor markets. At the same time, Chinese agriculture has been a distinctive "big country, small farmer" model since ancient times, so the impact of differences in agricultural production scale on spatial association networks is not obvious. The smaller penetration of financial development into the agricultural economy compared to other sectors may be the reason for the insignificant effect of differences in financial development on spatial association relationships.

6 Conclusion and implications

6.1 Conclusion

In our study, by examining the ALTFP of 30 Chinese provinces from 2001 to 2020, we explored the network characteristics and driving mechanisms of spatially linked relationships with the help of UCINET visualization tools and social network analysis methods, and we mainly obtained the following conclusions and insights.

1) In terms of network structural characteristics, the spatially linked network of low-carbon development in China's agriculture has broken the traditional geographical limitation of "neighbors as friends" and exhibited a complex network of links. However, the overall network structure is relatively loose, and there is still much room for improving the coordinated development of low-carbon agriculture between provinces. The connectivity and robustness of the network are gradually strengthened, but the network still has a certain hierarchical gradient and some redundant relationship numbers, the network structure needs to be further optimized. In terms of regional network structure characteristics, the correlations of China's agricultural low-carbon development during 2001–2020 tend to occur among the four major plates in the east, center, west, and northeast, with a smaller degree of factional forestry, the eastern region is more connected to other regions, while there are fewer connections between the central, western and northeastern. Individual network characteristics show that there is a significant "Matthew effect" in China's agricultural low-carbon development. The eastern provinces of Shanghai, Beijing, Tianjin, Jiangsu, Zhejiang, and Fujian are at the heart of the entire network and have a stronger role in allocating resources needed for agricultural low-carbon development, while remote provinces such as Xinjiang, Jilin, Liaoning, and Anhui are at the edge of the network and have a weaker ability to access resources for agricultural low-carbon development.
2) The analysis of the network structure effect shows that network structure has a significant effect on the level of low carbon in agriculture, and increasing the overall network density and network relevance, decreasing the network hierarchy and network efficiency can significantly increase the ALTFP. The weakening of regional factional forestry is conducive to promoting low-carbon agricultural development. The province's central position in the network and its dominance and control over resources and factors in low-carbon agricultural development are conducive to increasing the ALTFP. The panel quantile regression model further verified the reliability of the above findings.
3) The QAP results show that the spatial proximity of provinces, the widening of differences in urbanization levels and differences in financial support for agriculture, and the narrowing of differences in the educational attainment of the rural labor have significantly contributed to the formation of provincial spatial linkages And differences in the level of financial development, differences in the level of marketization, differences in the efficiency of agricultural irrigation water use, differences in the structure of agricultural industries and differences in the scale of agricultural production do not have significant effects on the spatial correlation network of ALTFP, and their response mechanisms and response effects need to be further explored.

6.2 Implications

Firstly, inter-provincial geographical proximity can break down barriers to resource flows and facilitate provincial flows of low-carbon development in agriculture, for example, the development of city clusters such as Yangtze River Delta and Pearl River Delta is conducive to promoting the formation of related networks, so the linkage leading effect of China's city clusters and metropolitan areas should be accelerated. At the same time, it is necessary to promote the construction of agricultural low-carbon development demonstration areas, strengthen the interconnection of core and peripheral regions, eliminate the Matthew effect of agricultural low-carbon TFP, and give full play to the role of the "leader" of Beijing-Tianjin-Hebei and the Yangtze River Delta, which are regions with high levels of economic development, to radiate and drive the balanced development of the region, to narrow the gap between provinces in the spatially linked network of green economy in terms of capital, technology, and management methods, effectively reduce the network hierarchy, and realize the spatial synergy of green economy development.

Secondly, the central and western regions need to strengthen spatial ties with developed regions, ride on the coattails of the urbanization process, undertake the overflow of factor resources such as capital, industry, and technology from the eastern regions, and formulate more precise regional policies to enable the flow of factors to the central and western regions under the guidance of market mechanisms. At the same time, the construction of agricultural low-carbon development demonstration regions within the central and western regions should also be accelerated to form a polycentric pattern of agricultural low-carbon development, which reduces the rising transaction costs in the central and western regions and accelerates the flow of agricultural resources and factor capital in the marginal regions.

Finally, local governments should clarify the position and role of each region in the low-carbon development of agriculture, give full play to the role of government macro-control and market regulation mechanisms to promote the spatial correlation of green economic development, minimize the intervention in the financial system leading to financial distortion, and effectively guide the financial expenditure to support the low-carbon development of agriculture. At the same time, we should also focus on the improvement of education level in the backward areas and gradually narrow the gap between the educational level of the labor force in the backward areas and the developed areas.

6.3 Research deficiencies and future directions

Although the paper makes an obvious contribution to the low carbon development of agriculture, there are still some limitations: First, considering the limitation of data availability, this paper examines the spatial correlation network of low carbon development of Chinese agriculture from the provincial level, and the results are relatively rough; in the subsequent research, the data should be further explored in depth to refine the research results and make the paper more valuable in the application. Second, for the analysis of spatially linked network drivers of low carbon development in agriculture, the paper selects nine aspects of influencing factors, and inevitably there are other influencing factors, such as climate and soil type, which should continue to be explored more deeply in future studies.

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.

Author contributions

FF conducted data collection and measurement, and wrote the text. JZ conceived of the research, made the structure, supervised this research work. LZ provided guidance on the methodology and an overall grasp of the logical structure of the text provided. JD provided a great deal of assistance in data collection and organization, and in writing the text.

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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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Nomenclature

Super-RSBM Super-efficiency Ray Slacks-Based Model

GML Global Malmquist-Luenberger

RGML Super-RSBM method to characterize the low carbon TFP level in agriculture

RSBM-GML Super-efficiency Ray Slacks-Based Model - Global Malmquist-Luenberger

ALTFP low carbon TFP of agriculture.

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Does e-commerce participation affect green agrotechnology adoption among reservoir resettlers? The case of China's Three Gorges Reservoir area

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This study explores how promoting e-commerce participation impacts the adoption of green agrotechnology by resettlers in China's Three Gorges Reservoir area and helps rural revitalization and the realization of value from ecological produce. First, we combine induced innovation model theory with the risk perception factor of expected utility theory. A model of resettlers' green agrotechnology adoption under different levels of e-commerce participation is constructed, and research hypotheses are proposed accordingly. Survey data gathered from resettled farmers in Zigui, the first county of the studied area, are tested empirically with an ordered probit model. The results show first, that e-commerce participation significantly and positively affects the level of green agrotechnology adoption at the 1% level; and second, that expectations of the ecological value of agricultural products and the agrotechnology support provided by e-commerce are important driving factors. The promotion effect of different modes of e-commerce participation on agrotechnology adoption differ. The risk-averse behavior of resettlers can weaken the promotion effect of e-commerce participation on agrotechnology adoption.

KEYWORDS

e-commerce participation, green agrotechnology adoption, risk perception, reservoir resettlers, ordered-probit model

1 Introduction

The increasing number of hydropower plants being built around the world to achieve clean energy has led to a large number of compulsory population movements, resulting in the emergence of resettled farmers as a group. In accordance with the World Bank's resettled guidelines, rural resettlers in China are mostly resettled in the back-to-back mode of "returning land to land and agriculture to agriculture" for the sake of continuing their original livelihoods (Yan et al., 2018). However, due to the limited resource-carrying capacity of the Three Gorges Reservoir area, the arable land available there has become increasingly scarce. Most of the compensation land received by resettlers is fragmented and low in quality, causing not only limited output but also significant increases in the cost of crop cultivation (Zhang 2021). Chinese rural re-settlers' per capita income was only about 76% of that of ordinary farmers in 2014. Therefore, fewer than 30% of resettlers actually cultivate the land that the government transferred to them at a high cost, and many tend to abandon the land and go out to work instead (Ni and Shao 2013). Currently, in the context of natural capital stock constraint, the only way to guarantee that resettlers can increase their income from local farming is by applying and promoting green agrotechnology.

Green agricultural technology aims to solve environmental problems and promote sustainable agricultural development. It will improve the soil by reducing pollution, leverage the ecological value of agricultural products, and raise crop yields (Zuo and Fu 2021). The waste of resources and environmental pollution caused by the unscientific nature of traditional agricultural technology hinders the green development of agriculture in resettlement areas. Achieving a green transformation of agricultural development is an important way to solve the current agricultural development challenges in resettlement areas. As resettlers' livelihoods are highly vulnerable and they struggle to withstand the ex-post effects of risks, they mainly choose to avoid risk. Their conservative behavior in agricultural production hinders the adoption of green agrotechnology to a certain extent. Therefore, a long-term mechanism of green agrotechnology adoption is needed to solve the current problem of low level of green agrotechnology in resettlement areas and to achieve sustainable development of resettlement areas and individual income of resettlers.

For involuntary resettlers with impaired livelihood capital and broken social networks of origin, rural e-commerce, a new rural industry with convenient participation channels and an almost zero threshold for resource consumption, has become the first choice to improve the production and marketing of agricultural products (Yin and Choi 2022). For example, in the Three Gorges Reservoir area of China, the town of Xingshan is located in a mountainous area with a low land stock, but resettlers have achieved an average daily sale of 100,000 kg of citrus by using live streaming. The strong development of Internet technology has enriched agricultural e-commerce models, with traditional e-commerce, social e-commerce, and live e-commerce all expanding in scale (Chen et al., 2022). Heterogeneous participation in rural e-commerce brings innovation to the traditional agricultural products business model and concept while effectively enhancing the income of resettled households. At the same time, the online sales model requires quality standardization and ecological branding, which will certainly promote the application of green agrotechnology and bring high-quality change to resettled areas (Xiao et al., 2021).

Current research on empowering rural agents to promote the adoption of green agrotechnology focuses on three aspects. The first is the promotion of environmental regulations and government subsidies, which can be used to guide technology application behavior in agricultural production. Reducing the costs involved in such production will support and guarantee the sustainable application of green agrotechnology (Dong et al., 2022). Second, research has explored the contribution of regional resource endowments, where the level of development, farming history, and soil quality are direct factors determining individual adoption intentions and behaviors (Zeng et al., 2019; Wu and Zhou 2021), while population aging and the stock of agricultural technicians have obvious indirect effects (Natkhov and Vasilenok 2021). A third stream, focusing on the role of rural households and individual characteristics, has found that the degree of green agrotechnology adoption is constrained by farmers' relational capital (Wang et al., 2020), socioeconomic status (Bidogeza et al., 2009), and learning and training opportunities (Chatzimichael et al., 2014).

In contrast, risk preferences play a dominant role in individual production decision behavior (Gao and Niu 2019), and risk perceptions, in turn, positively moderate the degree of association between risk preferences and agrotechnology adoption (Qiu et al., 2020). For example, perceived risk from agricultural production affects the use of irrigation technology (Koundouri et al., 2006), fertilizers (Adnan et al., 2019), *etc.* Since it is difficult for individuals to fully understand the benefits associated with the use of green agrotechnology, they tend to have doubts about the risks they need to take in technology adoption (Chavas and Nauges 2020). However, further studies have shown that farmers may use subjective risk judgements to weigh the pros and cons; that is, there is a negative relationship between the perceived risk of using green agrotechnology and the probability of adoption (Duong et al., 2019). The research outlined above is limited by the fact that the paths between variables have only been tested empirically, while specific influence mechanisms have not yet been theoretically deduced. Hence, such mechanisms are based only on the summary of phenomena and experiences and lack a scientific basis. Further exploration is required of such mechanisms and the paths whereby the interactive feedback model of e-commerce operation–agrotechnology application–income enhancement can be realized.

The Chinese government has implemented appropriate support policies for Reservoir resettlers, and the livelihood level and social integration of this group have been significantly improved. Ensuring the sustainable self-development of involuntary project resettlers has attracted research attention globally (Karimi and Taifur 2013). The current research was conducted as follows. First, we constructed a model of the benefits of green agrotechnology adoption by resettled households under different e-commerce participation scenarios, based on utility optimization theory and induced agricultural technological innovation theory. Second, we introduced risk perception as a moderating variable and combined it with expected utility theory to improve the multi-factor influence mechanism model of resettled technology adoption. Third, we proposed research hypotheses according to the theoretical derivation and empirically tested the theoretical model using the ordered probit model with survey data gathered from resettled farmers in Zigui, Hubei province, China, the first county in the Three Gorges Reservoir area. Next, we explored how the promotion of rural e-commerce participation affects the adoption of green agrotechnology by resettlers and the core elements within this process and investigated the perturbing influence of the particular risk preferences of involuntarily relocated populations in regard to promoting modern agricultural technology and achieving sustainable livelihood development. Last, we provide support for decision making in regard to compensating and supporting resettlers in water conservancy and hydropower projects.

2 Theories and hypothesis

In the theory of agricultural supply chain integration, in response to the impact of the agricultural business segment on the production segment, induced agricultural technological innovation theory was proposed at the start of the 20th century. This theory argues that the business model is closely related to agricultural technological innovation (Cowan et al., 2015) and that a proposed increase, decrease, or change of production and business factors will necessarily bring about technological innovation (Schultz 1987). Accordingly, it is clear that the promotion of Internet technologies and the development of rural e-commerce will inevitably promote changes in production by farmers, namely the use of green technologies in agriculture. On the one hand, the combination of e-commerce and the digital economy completes the construction of a digital system for the agricultural industry which is more conducive to the value-added and market demand transfer of green agricultural products and allows for more convenient mining and teaching of green agricultural technologies (Fu and Zhang 2022). On the other hand, the expansion of agricultural product sales by e-commerce and logistics platforms has led to a surge in the number of end customers with green consumption needs. The trend of standardization and branding of agricultural products has led to increasingly stringent requirements for the production process, which has also forced the improvement and standardization of the use of resettled agricultural technologies (Dong et al., 2021) as shown in Figure 1.

In the process of compulsory relocation, Reservoir resettlers lose their livelihood capital, livelihood capacity, and social network. Thus, the focus of subsequent development has been on how to achieve maximum benefits under resource constraints (Zhang 2021). It is a requirement of the principle of developmental resettled for hydropower projects in China that the post-resettled production and living standards of resettlers should not be lower than those before relocation. Therefore, whether resettled farmers can promote the application of green agrotechnology in agricultural production after participating in rural e-commerce is mainly determined by the related profit, so it can be judged according to the profit function corresponding to different participation situations of e-commerce, as shown in Eq. 1.

$$\pi_i = TR(Q) - TC(Q) \tag{1}$$

where π_i is the profit of resettlers selling household agricultural products; $i = 0$ means through an online e-commerce channel, and $i = 1$ means along the traditional offline channel. Q is the agricultural production level of resettled households in the resettled area, $TR(Q)$ is the total income derived from agricultural cultivation, and $TC(Q)$ is the corresponding total expenditure. Here, it is assumed that the production level Q of resettled households can be expressed by Eq. 2.

$$Q = f[I(g), g] \tag{2}$$

In the above equation, g is the degree of green agrotechnology adoption by resettled households, and I is other agricultural production factor inputs. The degree of households' inputs is closely related to the level of agrotechnology they use, so the latter can be expressed in the functional form $I(g)$. Assuming that the price of agricultural production factor I is P^0 and the unit price of green agrotechnology input is P^1, the profit of resettled agricultural output can be shown as in Eq. 3.

$$\pi_i = TR(Q) - TC(Q) = P_i Q - P^0 I(g) - P^1 g \tag{3}$$

At this point, it is necessary to find the optimal level of adoption of green agrotechnology for resettlers under the profit maximization condition, which is the derivative of profit π_i to the degree of adoption of agrotechnology g as shown in Eq. 4.

$$\frac{d\pi_i}{dg} = P_i \cdot \left[\frac{\partial Q}{\partial I} \cdot \frac{dI}{dg} + \frac{dQ}{dg}\right] - P^0 \cdot \frac{dI}{dg} - P^1 = 0 \tag{4}$$

In the above equation, $P_i \cdot dQ/dg$ can be regarded as the marginal benefit of green agrotechnology adoption by resettlers, denoted as MR_i, while $P^0 \cdot dl/dg + P^1$ is the marginal cost of agrotechnology adoption, denoted as MC_i. While the network direct sales model allows customers to sell their products directly, it also allows customers to obtain ecological and high-quality agricultural products more conveniently (Tian et al., 2022). Then it feeds this demand to resettled households quickly, which becomes a source of motivation for this group to apply green agricultural technology. For example, in the resettled area of Guojiaba Township, Zigui County in the Three Gorges Reservoir area, a water and fertilizer integrated navel orange planting base was built with the help of an e-commerce platform, and the track from the orchard to the road was electrified and a full production cycle traceability system with an integrated QR code was designed.

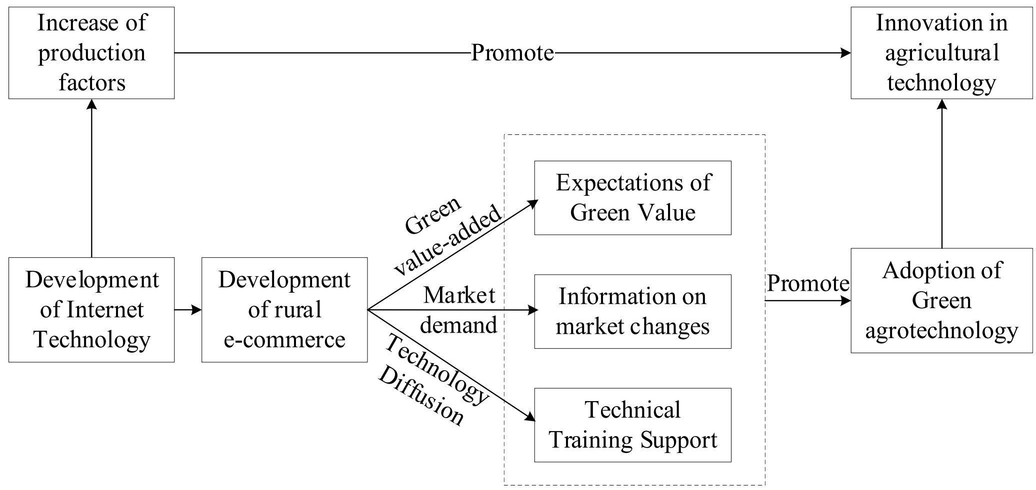

FIGURE 1
Analytical framework based on induced agricultural technological innovation theory.

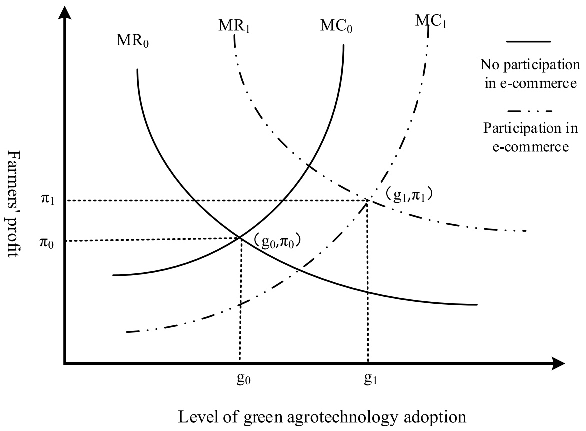

FIGURE 2
Linkages between e-commerce participation and resettlers' green agrotechnology adoption.

The results calculated from Eq. 4 is shown in Figure 2. In the case of resettled households participating in e-commerce, when $MC_1 = MR_1$, the optimal green agrotechnology adoption level is g_1, and when resettled households do not participate in e-commerce, the optimal value of green agrotechnology adoption at this point can be obtained from $MC_0 = MR_0$ as g_0. The current participation of resettlers in e-commerce will significantly increase the sales price of agricultural products. For example, the traditional channel sale price of pomegranate in Yunnan reservoir area of the lower Jinsha River hydropower station in 2021 was 0.5 USD/kilogram (kg). While through e-commerce do boutique retailing, it can be sold at 0.62 USD/kilogram (kg), an increase of more than 20%. So, when $P_1 > P_0$, there is $g_1 > g_0$, and the following research hypothesis can be proposed.

Hypothesis 1. Participation in e-commerce has a catalytic effect on resettled growers' green agrotechnology adoption behavior.

Different e-commerce participation models will have different benefits for resettled households as the participating subjects and circulation links vary. This paper classifies resettled households' e-commerce participation model as either platform e-commerce or social e-commerce, according to the survey data. The platform e-commerce model refers to resettled households selling through online trading platforms, such as Taobao and Jindong. The social e-commerce model refers to such households selling through a network of acquaintances to form a fixed source of online customers, such as through WeChat or QQ. The platform e-commerce model may obtain higher product revenue as a large number of merchants are participating: While the platform products are highly competitive barriers to entry, the requirements for technical investment are also higher. The social e-commerce model has price advantages, but resettled households have a limited network group of acquaintances, and the fact that e-commerce has a limited effect on increasing income leads to less willingness to adopt technical innovation and lower rates of green agrotechnology adoption. Accordingly, the following research hypothesis can be proposed.

Hypothesis 2. There are differences in the promotion of green agrotechnology adoption among resettled households according to various e-commerce participation models, with the platform e-commerce model outperforming the social e-commerce model.

However, a single profit-seeking factor is not sufficient in explaining the motivation of resettled households when they adopt green agrotechnology (Adnan et al., 2021). The increased vulnerability of livelihood and the relatively scarce livelihood capital led to a weakening in the ability of involuntary resettled groups to tackle risks to their livelihoods (Gong et al., 2020). However, the application of green agrotechnology may also give rise to additional risks, including technological, natural, and market risks. For example, compared with chemical pesticides, organic pesticides are difficult to operate and highly targeted. Resettlers faced with planting new crops in resettled areas may be vulnerable to yield reduction after application of a new technology. Especially if they are not familiar with pesticide selection, application dosage, and application time (Fang et al., 2021). In addition, resettlers whose original social networks are a great distance away from the resettled area and who have poor information channels may face failure to achieve high quality and high prices for their agricultural products, and with high technology costs (Lu et al., 2018). Therefore, resettlers have a lot of uncertainty when adopting green agrotechnology, and thus perceive the existence of risks, and in view of their relatively weak risk tolerance, they are mostly risk-averse subjects. In other words, the greater levels of risk perception in the resettlers' technology adoption behavior will directly affect the role played by e-commerce in the promotion of such behavior. From the expectation-utility theory, the utility function of resettlers' participation in rural e-commerce is shown in Eq. 5.

$$U(W-e) = E[U(W+\varepsilon)] \tag{5}$$

Where U and E are the utility and expected utility functions of resettled households, respectively, W is the production and marketing input, ε is the stochastic return, and e is the risk premium, which indicates the degree of resistance to green agrotechnology among resettled e-commerce participants. In order to analyze whether risk perception affects the propulsive effect of e-commerce on agrotechnology adoption behavior, the relationship between resettled risk perception and risk preference e must first be clarified. It is assumed that the benefit utility $U(W)$ of resettled e-merchants is second-order derivable. Then a Taylor series expansion is carried out for both sides of Eq. 5 based on the point W. The results are shown in Eq. 6.

$$E\left[U(W) + U'(W)\varepsilon + \frac{1}{2}U''(W)\varepsilon^2 + R\right] = U(W) + U'(W)e + R \tag{6}$$

R in the above equation is the higher order remainder term of Eq. 6, and the process of transforming the resettled participation in the electric utility U in Eq. 5 by the equation is shown in Eq. 7.

$$U(W-e) = U(W) + U'(W)e + R \approx U(W) + U'(W)e \tag{7}$$

Similarly, an equation transformation of the resettled expected utility function E in Eq. 5 is shown in Eq. 8.

$$\begin{aligned} E[U(W+\varepsilon)] &= E\left[U(W) + U'(W)\varepsilon + \frac{1}{2}U''(W)\varepsilon^2 + R\right] \\ &\approx U(W) + U'(W)E(\varepsilon) + \frac{1}{2}U''(W)E(\varepsilon^2) \end{aligned} \tag{8}$$

Since resettlers are mostly risk-averse after experiencing loss of livelihood, R is basically negligible and has $E(\varepsilon) = 0$, therefore at this point, $E(\varepsilon^2) = Var(\varepsilon)$. According to Eqs 5, 7, 8 are equivalent by association, which leads to Eq. 9.

$$U(W) + \frac{1}{2}U''(W)Var(\varepsilon) = U(W) - U'(W)e \tag{9}$$

An equation transformation of Eq. 9 can locate the willingness to resist green agrotechnology e of e-commerce resettled households, as shown in Eq. 10.

$$e = -\frac{1}{2}\frac{U''(W)}{U'(W)}Var(\varepsilon) = \frac{1}{2}k(e)Var(\varepsilon) \tag{10}$$

It can be calculated that $U''(W)/U'(W) = k(e)$ in the above equation, while $Var(\varepsilon)$ represents the external factors affecting resettlers' returns. This is the variance of random returns, which can be considered as being the perceived income risk held by resettled households. In the case that resettled households tend towards risk-aversion, $k(e)$ is relatively stable. If the degree of resettled risk perception $Var(\varepsilon)$ is higher, the value of e increases, indicating that resettlers are more resistant to green farming techniques. According to the above analysis, the following research hypothesis can be proposed:

Hypothesis 3. Individual risk perceptions will constrain the degree to which e-commerce participation promotes the adoption of green agrotechnology by resettled households.

3 Data, models and variables

3.1 Location selection and data sources

The Three Gorges Reservoir has flooded 260 km^2 of arable land, and there are 354,000 rural resettlers settled in the area. This has resulted in an extremely limited environmental capacity to produce food. Zigui County in Hubei, at the head of the Three Gorges Project Reservoir, is both a resettled area and classed as a "national poverty-stricken county," with 25% of its total population being Reservoir resettlers. As the climate and soil environment are very suitable for the growth of Navel oranges, Zigui County has become famous as China's "Navel Orange Township." Therefore, in recent years, through the Three Gorges resettled support funds and other promotional projects, Zigui County has been encouraged to adopt green agriculture. At present, the Zigui navel orange production area covers 23,200 ha and has an annual output of 605,000 metric tons. Across the area's 12 towns and 116 villages, about 198,000 people

TABLE 1 Number of resettled households' adoption of various green agricultural technologies.

Sample townships	Resettlers	E-commerce participation	Physical control	Pollution-free pesticides	Soil testing fertilizer	Laminated water control	Grafting	Fertilizer integration
Maoping	159	126	54	48	36	27	51	9
Guojiaba	240	153	126	129	126	24	192	21
Guizhou	186	81	105	114	93	24	156	18
Shuitianba	75	39	51	30	36	3	57	18
Tatal	660	399	336	321	291	66	456	66

are engaged in related industries, and this is the only national citrus production area that produces fresh fruit throughout the year.

In order to solve the difficulties caused by the lack of land to compensate resettlers in the county, as well as a lack of social resources and the low premium capacity of agricultural products, Zigui County took the lead in innovating an e-commerce development model in 2014 and was selected as one of the second batch of national "e-commerce-demonstrating rural counties" in 2019. In recent years, the proportion of online sales of Navel oranges has accounted for about 55% of total sales, and the per capita net income of orange farmers increased from 1,967 USD in 2014 to 3,372 USD in 2018, becoming an important way to enhance the income of resettlers. In addition, e-commerce promotes the adoption of solar pest control lights, water and fertilizer integration, Internet of Things (IoT, through which things are connected through the Internet) management, and other green agrotechnology, using networks to strengthen the ecological brand marketed as "a river of clear water, green mountains on both sides of the river, four seasons of fresh oranges."

The data used in this study come from the Navel orange electric business and green agrotechnical survey conducted in the resettlement area of Zigui County, Hubei Province during December 2020. The sampling points were selected from a total of 34 resettlement villages and groups in three towns and one township, namely Maoping Town, Guojiaba Town, Guizhou Town, and Shuitianba Township. At present, each of the four has an electric e-commerce logistics center, an e-commerce service center, and other infrastructure and service facilities and has several green agrotechnology demonstration orchards or planting bases, such as the Bajiaolou Green Technology Tour Park, the Flying Green Plant Protection base in Guogutai Village, Guojiaba Township, and the Alibaba Group's Future Farm in Choumushu Village, Shuitianba Township. All these were sampled.

The specific sampling method was to randomly select eight to 10 sample villages in each township, then randomly conduct household surveys. A total of 688 resettlers were interviewed. After samples with no response or doubtful key information were excluded, 660 valid questionnaires were obtained. The number of resettled households' adoption of various green agricultural technologies is shown in Table 1.

According to the list of technical systems in the "Technical Guidelines for Green Agricultural Development (2018–2030)," resettled households mainly apply six types of green agrotechnologies: physical control technology, pollution-free pesticide technology, soil formula fertilizer technology, film and water control technology, water and fertilizer integration technology, and grafting technology. Of these, 120 households (18.2%) have adopted two kinds of technologies, and 249 households (37.7%) have adopted four or more kinds of technologies, which shows that green agrotechnologies are in the emerging stage in the resettlement area.

3.2 Model construction

Using Li et al. (2020) classification of degree of agrotechnology adoption, we divided resettlers' agrotechnology adoption into five categories, from low to high, and assigned them the following values: lower adoption = 1, low adoption = 2, moderate adoption = 3, high adoption = 4, and higher adoption = 5. Since, as an explanatory variable, the degree of resettlers' agrotechnology adoption g is a multi-valued ordered variable, we used the ordered probit model to explore the influencing factors involved, and the underlying regression model constructed is shown in Eq. 11.

$$g_i^* = \alpha_1 + \beta_1 EP_i + \beta_2 GPE_i + \beta_3 TTS_i + \lambda_1 CV_i + \sigma_i \qquad (11)$$

In Eq. 11, EP_i, GPE_i, and TTS_i represent e-commerce participation, agricultural price expectation, and agrotechnology training of the ith resettled household, respectively, while CV_i represents a series of control variables and σ_i is a random disturbance term. g_i^* is a latent variable of the degree of green agrotechnology adoption of resettled household i. Let C1<C2<C3<C4<C5 be the threshold, then g_i values can be discretized by g_i^* as shown in Eq. 12.

$$g_i = \begin{cases} 1 & g_i^* \le C_1 \\ 2 & C_1 \le g_i^* \le C_2 \\ 3 & C_2 \le g_i^* \le C_3 \\ 4 & C_3 \le g_i^* \le C_4 \\ 5 & C_4 \le g_i^* \le C_5 \end{cases} \tag{12}$$

If the random disturbance term σ_i obeys the standard normal distribution, X is a vector of actual observations of sample households for all independent variables, and ϕ denotes the cumulative distribution function. The impact mechanism of each adoption degree is shown in Eq. 13.

$$\begin{cases} P(g_i = 1|X) = P(g_i^* \le C_1) = \Phi_1 \\ P(g_i = 2|X) = P(C_1 \le g_i^* \le C_2) = \Phi_2 \\ P(g_i = 3|X) = P(C_2 \le g_i^* \le C_3) = \Phi_3 \\ P(g_i = 4|X) = P(C_3 \le g_i^* \le C_4) = \Phi_4 \\ P(g_i = 5|X) = P(C_4 \le g_i^* \le C_5) = \Phi_5 \end{cases} \tag{13}$$

After an ordered-probit model is constructed in Eq. 13, the regression coefficients can be estimated using the maximum likelihood estimation (MLE) method. In addition, we conducted additional analyses independent of the probit model. To analyze the extent to which e-commerce participation drives the adoption of agricultural technologies, we analyze the marginal effects of each independent variable, as shown in Eq. 14.

$$\partial P(g_i = n|X)/\partial x_j = -\Phi_n \beta_j \tag{14}$$

Where $n = 1,2,......5$ represents the five degrees of resettled green agrotechnology adoption, x_{ij} is the jth independent variable of sample i, and β_{ij} is the coefficient to be estimated for x_{ij}. The marginal effects were analyzed according to the sign and coefficients of the results.

3.3 Variable selection

3.3.1 The dependent variables of this paper is resettled households' adoption of green technologies in navel orange cultivation

The specific measurement has six categories of green agricultural technologies adopted by resettled households, and the value is assigned as 1 if adopted, and 0 if not. Due to variations in natural capital among resettled households, it is not suitable to use equal weighting among the categories because of limitations placed on the use of different green agricultural technologies. Therefore, the four dimensions of economic benefits, resource saving degree, ecological benefits, and operational feasibility are considered comprehensively, and the entropy value method is applied to determine their weighting coefficients. The steps are as follows: 1)Calculate the indicator weight $p_{ij} = X_{ij}/\sum_{i=1}^{m} X_{ij}$ for item i under the jth indicator of resettled household X_{ij}, where m is the number of evaluation dimensions. 2) Measure the entropy value of indicator j $e_j = -\sum_{i=1}^{m} p_{ij} \ln p_{ij}/\ln m$. 3) Derive the entropy weight $w_j = (1 - e_j)/\sum_{j=1}^{n}(1 - e_j)$ of the jth indicator. 4) Obtain the weight coefficients by calculating the weight of each secondary indicator of the evaluation dimensions, as shown in Table 2.

3.3.2 Independent variables

According to the model deduction of the previous theoretical analysis, it can be seen that the participation behavior of e-commerce. The expected sales price of agricultural products are the keys to promoting the adoption of green agrotechnology among resettlers. The improvement of agrotechnology application capacity through training is also an important factor (Liu et al., 2022).

3.3.3 Moderating and controlling variables

According to the aforementioned theoretical model, it is clear that the perceived risk factors of resettled households have an impact on e-commerce's promotion of the use of agrotechnology. These involve various aspects and varying degrees of perception, such as natural conditions, market environment, and technical capacity. According to previous studies, there are two main types of control variables. One is demographic characteristics, including gender, age, and the level of education of respondents. The other is household endowment, including the maximum years of education of members, the proportion of household labor force, annual household income, navel orange planting area, and support from local cooperative organizations.

The definition and descriptive statistics of each variable are shown in Table 3, in which the mean value of adoption of green agrotechnology is 1.763. The overall application degree still needs to be improved; however, participation in e-commerce is more than half, indicating that resettlers generally have enthusiasm to engage in e-commerce. At the same time, the current support for training in the use of agricultural technology is still insufficient with the mean value is 0.414. The risk perception of the application of agricultural technology is around the mean value, which needs to be controlled and further development of e-commerce is required to promote the popularity of green agricultural technology in resettled areas.

4 Empirical results

4.1 Impact of e-commerce participation behavior on the degree of green agrotechnology adoption

Before testing the role of e-commerce participation behavior in the promotion of the application of resettled farming techniques, a multiple cointegration test between the relevant independent variables was required. The resulting variance inflation factor (VIF) was far below 10, without cointegration

TABLE 2 Evaluation indicators and weights of the degree of adoption of various types of green agrotechnology by resettled households.

Target layer	Level 1 indicators	Secondary indicators	Secondary indicator weights	Weighting of primary indicators
Degree of adoption of green agrotechnology	Physical control technology	Economic benefits	0.019	0.075
		Resource conservation degree	0.019	
		Eco-friendly effect	0.018	
		Operability	0.019	
	Pollution-free pesticide technology	Economic benefits	0.018	0.070
		Resource conservation degree	0.018	
		Eco-friendly effect	0.017	
		Operability	0.017	
	Soil testing and fertilizer technology	Economic benefits	0.014	0.056
		Resource conservation degree	0.014	
		Eco-friendly effect	0.014	
		Operability	0.014	
	Lamination and water control technology	Economic benefits	0.096	0.383
		Resource conservation degree	0.095	
		Eco-friendly effect	0.096	
		Operability	0.096	
	Water and fertilizer integration technology	Economic benefits	0.095	0.386
		Resource conservation degree	0.098	
		Eco-friendly effect	0.096	
		Operability	0.097	
	Grafting and splicing technology	Economic benefits	0.007	0.030
		Resource conservation degree	0.007	
		Eco-friendly effect	0.007	
		Operability	0.009	

problems. We then examined whether the original data satisfied the parallel regression hypothesis and found that the chi-square value was not significant. This meant the hypothesis was valid for analysis using the ordered-probit model. Finally, regression models were constructed when no-control variables (Model I), household head characteristics (Model II), and household head characteristics and household endowment (Model III) were added. The regression models are shown in Table 4.

As shown in Table 4, e-commerce participation significantly and positively influenced resettled navel orange growers' green agrotechnology adoption behavior at the 1% level, i.e., Hypothesis 1 holds. To analyze the influence mechanism, the relationship between e-commerce participation behavior, agricultural price expectation, and technical training support was further investigated here, as shown in Table 5. The regression results show that there is a significant positive correlation between participation in e-commerce and factors that support technology adoption support regarding such as price expectation of agricultural products and technical training support.

According to the model regression results above, participation in e-commerce has a significant positive effect on resettled households' adoption of green agrotechnology. Specifically, various government subsidies and agricultural policies increased their green agricultural product price expectations after participating in e-commerce. For example, Zigui County has successively issued documents such as "Implementation Opinions on Accelerating E-commerce Development" and "Implementation Plan of E-commerce in Rural Areas Project," which have greatly enhanced the information used by resettlers in their agrotechnology inputs. At the same time, resettlers have been given more technical training opportunities. For example, platforms such as Suning University and Jingdong Business School dispatched lecturers to

TABLE 3 Definition of variables and descriptive statistics.

Variable types	Variable name	Variable definition and assignment	Average	Standard deviation
Dependent variable	Level of adoption of green agrotechnology	Comprehensive calculation of the application of each type of agrotechnology (entropy method)	1.763	1.113
Independent variables	E-commerce participation	Participation = 1; No participation = 0	0.605	0.490
	Green product price expectations	Very low = 1; relatively low = 2; average = 3. relatively high = 4; very high = 5	3.436	0.648
	Technical training support	Accepted = 1; Not accepted = 0	0.414	0.494
Moderating variables	Risk perception	Perceived risk in green agrotechnology application: very small = 1; relatively small = 2; average = 3; relatively large = 4; very large = 5	2.782	1.076
	Gender	Male = 1, Female = 0	0.664	0.474
	Age	Actual age (years)	48.514	11.316
	Education level	Years of education (years)	9.777	2.925
Control variables	Maximum number of years of education for members	Maximum number of years of education for family members (years)	12.891	3.059
	Household labor force ratio	Ratio of labor force population to total population	0.725	0.235
	Annual household income	Total household income in 2020 (USD)	1.892	2.272
	Orange planting area	Household-owned orange cultivation area in 2020 (hectare)	0.7367	4.5678
	Local partner organizations support	Yes = 1; No = 0	0.164	0.371

TABLE 4 Regression results of the impact of green farming technology adoption among resettled orange growers.

Variable types	Variable name	Model I	Model II	Model III
		Coefficient (robust standard error)	Coefficient (robust standard error)	Coefficient (robust standard error)
Independent variables	E-commerce participation	0.821*** (0.191)	0.793*** (0.210)	0.859*** (0.211)
	Green product price expectations	0.647*** (0.135)	0.648*** (0.135)	0.664*** (0.136)
	Technical training support	0.516*** (0.168)	0.533*** (0.169)	0.481*** (0.175)
Control variables	Risk perception		−0.217 (0.176)	−0.151 (0.182)
	Gender		0.003 (0.009)	0.002 (0.010)
	Age		0.026 (0.035)	0.029 (0.037)
	Education level			0.002 (0.037)
	Maximum number of years of education for members			−0.164 (0.369)
	Household labor force ratio			−0.021** (0.009)
	Annual household income			0.001 (0.001)
	Orange planting area			−0.081 (0.228)
Pseudo-R^2		0.1467	0.1505	0.1635
Observed values		660	660	660

Note: *, **, and *** are statistically significant at the 10%, 5%, and 1% levels, respectively.

12 townships in Zigui County to teach e-commerce production and operation.

Based on the Hypothesis 1 test, the degree of resettlers' agro technology adoption under the role of each factor was further analyzed to explore whether the marginal effects of different degree types affected were sensitive, as shown in Table 6.

The results in Table 6 show that the percentage of resettled households with low technology adoption will decrease by 25% after they participate in e-commerce, while resettled households with moderate, higher, and high adoption will increase by 6.3%, 3.7%, and 7.4%, respectively. It is confirmed that the awareness and adoption of green farming techniques among resettlers are

TABLE 5 Correlation between e-commerce participation and green agrotechnology adoption support elements for resettled households.

Dependent variable		Green product price expectations	Technical training support
Independent variables	E-commerce participation	0.733*** (0.180)	0.542***(0.209)
Control variables		Controlled	Controlled
Pseudo-R^2		0.575	0.0988

TABLE 6 Marginal effects of each influencing factor on the degree of resettlers' adoption of agricultural technology.

	Very low adoption type	Low adoption type	Moderate adoption type	High adopted type	Very high adoption type
E-commerce participation	−0.252*** (0.052)	0.076*** (0.017)	0.063*** (0.018)	0.037** (0.015)	0.074*** (0.024)
Green product price expectations	−0.198*** (0.037)	0.060*** (0.015)	0.050*** (0.013)	0.029*** (0.011)	0.059*** (0.017)
Technical training support	−0.158*** (0.049)	0.048*** (0.017)	0.040*** (0.015)	0.023** (0.010)	0.047*** (0.018)

TABLE 7 Differences in the impact of different e-commerce participation models on resettlers' green agrotechnology adoption.

Group	Processing effects	Processing group	Control group	Difference	Standard error	*t*-test value
Overall sample	ATT	2.092	1.565	0.527	0.210	2.50
Platform e-commerce model	ATT	2.551	1.265	1.286	0.319	4.03
Social e-commerce model	ATT	1.815	1.284	0.531	0.258	2.06

enhanced under the e-commerce model. Resettled households with a low level of green agrotechnology application also decreased by 19.8% and 15.8%, respectively, as the price of agricultural products improved and agrotechnology training grew in popularity, but it was not as significant as the effect of e-commerce participation.

4.2 The impact of e-commerce participation model on the degree of adoption of green agricultural technology

To analyze the heterogeneity in the impact of different e-commerce participation models, this paper further empirically tested the impact of e-commerce participation models on resettled households' green farming skills. Statistics found that, among the sampled households participating in e-commerce, 153 (38.3%) used the platform e-commerce model sample and 246 (62.7%) used the social e-commerce model sample. The empirical results are shown in Table 7. According to the level of technology adoption classified by the previous section (1–5), from the overall sample, the degree of increase in agrotechnology adoption by farmers participating in e-commerce was 0.527, while the degrees of increase for the platform e-commerce and social e-commerce models were 1.286 and 0.531, respectively. The results indicate that the degree of increase for the platform e-commerce model was greater, suggesting that it could bring about a greater increase in agrotechnology adoption than the social e-commerce model.

4.3 Results of the moderating effect of risk perception

To verify the moderating role of risk perception in resettled agrotechnology adoption, Model IV was constructed by introducing the interaction term between e-commerce participation and risk perception. The results are shown in Table 8, which indicate that while e-commerce participation significantly increases the adoption of green agrotechnology, risk perception has a significant negative correlation to it. Indeed, the negative coefficient of the interaction term confirms that risk perception weakens the positive relationship between e-commerce participation and agrotechnology adoption, so Hypothesis 3 is valid.

TABLE 8 Analysis of moderating effects of risk perception.

Variable types	Variable name	Model IV	Model V	Model VI
		Coefficient (robust standard error)	Coefficient (robust standard error)	Coefficient (robust standard error)
Independent variables	E-commerce participation	1.971*** (0.562)	3.748*** (0.642)	2.220*** (0.425)
	Risk perception	−0.174** (0.151)		
	Green product price expectations		1.016*** (0.246)	0.558*** (0.154)
	Technical training support		0.744** (0.308)	0.352* (0.199)
Interaction items	E-commerce participation * Risk perception	−0.361** (0.184)	−0.799*** (0.195)	−0.518*** (0.129)
Control variables	Controlled	Controlled	Controlled	
Pseudo-R^2	0.1538	0.1991	0.1987	
Observed values	660	660	528	

For example, when the rainfall in Zigui and other places reached historical extremes in the summer of 2021, to ensure the taste of fresh navel oranges was maintained, the local migration management recommended the adoption of land mulching technology in the selenium-rich planting bases of Seven Princesses, Shi Wai Tian Yuan and other major e-commerce companies. However, if the residual film cannot be effectively recovered or is uncovered too late, the film will be left in the soil by weathering and decaying, and its long-term accumulation will result in serious damage and pollution to the soil. This means that the households with high soil quality requirements are cautious about employing this technology. Hypothesis 3 also illustrates that both the objective risk caused by external shocks and the subjective risk caused by incomplete information after relocation may have a significant impact on agricultural production decisions. Resettled households with weak resilience to potential risks to their livelihood, especially, are often forced to make careful trade-offs between low risk and high profit.

4.4 Robustness test

To test the robustness of our empirical results, one method was to construct another ordered-logit model (Model V) for the ordered variable of degree of resettlers' green farming technology adoption to conduct a regression analysis. The other was to extract 80% of resettlers' sample households and test them again through the ordered-probit model (Model VI). The results of both are shown in Table 8. As displayed in Table 8, there is essentially no difference in the sign (positive and negative values) of the regression coefficients for Models V and VI, or the significance level of the coefficients. This indicates the strong robustness of the hypotheses derived from the theoretical model, as well as the mechanisms of influence of the selected independent and control variables on the dependent variable.

5 Discussion

Based on relevant theories, this study reveals the impact of resettled households' e-commerce participation on their green technological innovations, determines the impact mechanisms, and conducts an empirical test. Our results summarize the results and experiences of modernizing involuntary among Three Gorges Reservoir area in China, which may provide a modellable case study for future rural revitalization in China. This may solve the sustainable livelihood problems of involuntary resettlers in other countries.

Due to the limited environmental capacity in the resettlement area, participation in social e-commerce among Reservoir resettlers is high, and it has gradually replaced the traditional agricultural cooperatives as the first choice to expand the distribution channels of agricultural products and generate family income. At the same time, although the adoption of green agrotechnology among resettlers is gradually expanding, adoption levels remain low to medium. Previous studies have mostly focused on the income-generating effects of e-commerce and the adoption factors and environmental effects of green agrotechnology (Takahashi and Muraoka 2019; Peng et al., 2021; Li et al., 2022), with less research on the interrelationship between the two, but the huge impact of e-commerce on agricultural production cannot be ignored. Our results show that e-commerce participation significantly increases the level of resettlers' green agrotechnology adoption, shrinks the proportion of households with low adoption, and increases the proportion of resettled households with high adoption. This is similar to the findings of Li et al. (2021). Specifically, agricultural price expectations and related agrotechnology training support from e-commerce were the most important agrotechnology adoption drivers, and the former was more sensitive, indicating that resettlers urgently need to rely on green agricultural development to cope with an industrial hollowing-out in the

Three Gorges Reservoir area due to natural capital loss and compensation resource constraints. However, green value-added agricultural products and e-commerce-assisted agrotechnical training mainly act on resettled households with low agrotechnical skills and, without the participation of e-commerce, will have limited impact effects.

Heterogeneous e-commerce participation models impact agrotechnology adoption differently. Many studies have shown that as e-commerce continues to develop, different e-commerce models, such as social e-commerce and platform e-commerce, are available (Luo 2022). Because the platform e-commerce model requires high household endowment, which is difficult for resettled households to afford, most such households choose the social e-commerce model. Chinese people value social relationships and are very good at using them (Zhang and Yang 2022). Resettled households share product information through social networks and word of mouth and can expand their product sales network more simply. Resettlers' awareness and adoption of green farming techniques have increased under various e-commerce models. Of these, platform e-commerce participation brings the greatest degree of enhancement; the traditional e-commerce participation model has more intense market competition and consumers' product requirements are higher (Heuer et al., 2015), which pushes resettled households to continuously improve the level of green agrotechnology adoption. In contrast, due to the limited network of resettled households' acquaintances, the demand for green agrotechnology adoption driven by social e-commerce is lower, as is the degree of improvement it brings.

Related studies have shown that uncertainty in the application and use of technologies when new technologies are introduced will also cause uncertainty in income (Chavas and Shi 2015; Hörner and Wolln 2022). Involuntary resettlers have a tendency to avoid livelihood risks and fear their own lack of resilience, thus, if they perceive risks in technology application, they are likely to weaken the green agrotechnology promotion effect brought about by e-commerce participation. Theoretical improvements and innovations are often not convincing to farmers (Bozzola and Finger 2020), especially when the technical barriers to green agrotechnology application are high or the effectiveness of use is uncertain, which will lead to higher risk perceptions in technology adoption and thus make e-commerce resettlers cautious about green agrotechnology.

Some shortcomings must be acknowledged. First, the agrotechnology selected in this paper is citrus cultivation technology, and the significance of other agricultural products still needs to be verified. Second, we tested limited factors influencing green agrotechnology. Government regulation and incentives, the role of markets, and individual capabilities still need to be further verified. Third, the rho-squared value is not at a high degree, so the model in this paper can continue to be improved. Subsequent studies can improve on the above aspects.

6 Conclusion and policy recommendations

Based on previous technology adoption theories, this paper constructs a theoretical model of green agrotechnology adoption by resettled households in the development of e-commerce in hydropower project reservoirs, taking into account the characteristics of Chinese involuntary project resettlers, the objective of maximizing expected returns, and the perceived risk to technology application posed by resettlers' livelihood risk resistance. Drawing on survey data from resettled households in Zigui, the first county in the Three Gorges Reservoir area, the hypotheses derived from the theoretical model were tested empirically by using the ordered probit model. The conclusions are as follows: Green agrotechnology has become more popular among resettlers, but the overall adoption level is still low; participation in e-commerce has a significant positive impact on the adoption of green agrotechnology at the 1% level. The ecological value expectation of agricultural products and the agrotechnology support provided by e-commerce are the most important driving factors, but their current effects are mostly limited to resettled households with a low level of agrotechnology. Compared with the social e-commerce participation model, platform e-commerce brings more significant improvements in technology adoption. The risk perception in resettled households' agrotechnology application weakens the promotion effect of e-commerce participation on agrotechnology adoption, while the risk perception of e-commerce participation weakens the promotion effect of the latter on the adoption of green agrotechnology.

Based on these findings, the following policy recommendations are proposed: 1) supporting fund should be used to improve network and logistics infrastructure. Through the combination of e-commerce policy and late-stage supporting system for resettlers, we can increase the participation rate of e-commerce and promote the application of green agricultural technology. 2) On the basis of the regional brand of the products in the resettled area, we embed the spirit of resettlers and create a special brand. On the one hand, it can realize the traceability of the whole growth cycle of agricultural products, and on the other hand, it can do the whole cycle of product development and expand a variety of products. This can enhance the agronomic value expectation of resettlers by adding value to agricultural products. 3) The government-led e-commerce associations in resettled areas should promote each other with the informal business organizations of resettlers formed by e-commerce platforms. It is necessary to provide green agrotechnology training more precisely. However, it is necessary to promote close interaction between resettlers and local residents through joint participation in e-commerce. Through small-scale technology demonstration and field guidance, the dissemination and exchange of tacit knowledge in the application of agricultural technology in resettler communities should be promoted. 4) To address the risk-averse tendency of reservoir resettlers in the application of green agricultural technology, the government of resettled areas should strengthen the publicity and popularize the knowledge of technical risks to avoid excessive precautionary behavior by resettlers. Meanwhile, the government should cooperate with insurance agencies to encourage farmers to purchase agricultural insurance policies. Such insurance policies are specifically used to share the technical costs incurred by resettler groups during the medium- and long-term growth periods of agricultural products and are incorporated into late-stage systems of risk sharing. This can reduce resettlers' hesitancy to adopt green agrotechnologies.

Data availability statement

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

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

All authors contributed to the study conception and design. The first draft of the manuscript was written by ZC, XZ, and FZ. All authors commented on previous version of the manuscript. All authors read and approved the final 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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Long term influence of alternative corn cropping practices and corn-hay rotations on soil health, yields and forage quality

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Modifications to continuous corn production systems can reduce environmental impacts and soil degradation, yet the social viability of these modifications is linked to the degree to which they also influence yields and crop quality. In this study, we focus on forage production systems and evaluate how yields, crop quality, soil health indicators, and associated ecosystem services are influenced by corn-hay rotation treatments, cover cropping, and tillage reduction in silage production using a unique 10-year dataset from Borderview Research Farm in Vermont, United States. Physical, chemical, and biological soil health indicators were monitored annually alongside yields and crop quality in a randomized complete block design experiment. We use a mixed model analysis of variance approach to demonstrate significant influences of time and treatments on yields, crop quality and soil health parameters (at $p < 0.05$). The winter rye cover crop treatment had no significant influence in this study. No-till significantly increased aggregate stability and had no significant effect on other metrics. When cover crop and no-till were combined, they significantly increased soil organic matter content, respiration and aggregate stability. The cover crop, no-till, and no-till cover crop combination treatments had no significant effect on yields or forage quality, suggesting these conservation practices can be adopted without sacrificing yields. Our study also found that corn-hay rotations can significantly increase soil organic matter, respiration, aggregate stability, and crude protein content compared to continuous corn, but they can negatively influence active carbon, total dry matter yield and digestibility. The length of rotation influences the degree to which corn-hay rotations maintain or reduce yields when compared to continuous corn. Shorter rotations of perennial forages (4 years of hay, 6 years of corn) can sustain dry matter yields that are not significantly different from continuous corn, but longer perennial forage rotations (8 years of hay, 2 years of corn) will significantly reduce overall dry matter yields. Among the treatments, no-till in combination with cover cropping in corn silage fields, and a rotation of 4 years of hay to 6 years of corn are likely to achieve the greatest overall benefits in forage production systems.

KEYWORDS

corn silage, soil health, no-till, cover crop, rotation, long-term, sustainable agriculture, perennial forage crop

1 Introduction

Human resource use currently exceeds planetary boundaries (O'Neill et al., 2018) and the sustainable intensification of agriculture is one of the most important pathways to ensure a livable future for humankind. Sustainable intensification broadly refers to increasing or sustaining the production of food while reducing inputs and sustaining the natural resource base (FA0, 2004) and while there are debates about the nuances of this definition, there is consensus that attempts to meet goals of sustainable intensification are rife with tradeoffs (Struik and Kuyper, 2017). Each production type, climate and food system context present different challenges and opportunities to meet goals of sustainability.

In recent years there has been renewed interest in the reintegration of crop and livestock systems as an alternative to continuous annual crop production. This diversification is hoped to sustainably intensify food production while benefiting producer income, crop production, soil properties, and increase environmental and socioeconomic resilience (Kumar et al., 2019). Benefits include closing the loop in nutrient cycles through the provision of manure, improving soil structure and water retention, and decreasing biocide requirements (Garrett et al., 2017). Integrating crops and livestock has been the norm in agricultural history, however, shifts in agricultural research and policy since the industrial revolution have resulted in more specialized and segregated approaches (Garrett et al., 2017). For example, United States farms were substantially more diversified and integrated in the 1970s than they are today. In 1974, 52% of the agricultural area and 19% of the farms utilized a crop-grazing rotation (USDA, 2007), but by 2012, this applied to only 7% of the farms and <2% of the area. Remote sensing studies confirm this trend toward homogenization, with mixed use areas being rapidly converted to continuous annual crops (Lark et al., 2015; Garrett et al., 2017).

The Intergovernmental Panel on Climate Change (IPCC) has identified crop-livestock integration as a resource-efficient and cost-effective agricultural adaptation strategy to sustainably maintain or increase food production (IPCC, 2018). Integrated crop-livestock systems have been shown to increase soil quality, crop yield, and economic returns compared to monoculture crop production in the Unites States (Sekaran et al., 2021). The majority of research to date has focused on the impacts of rotating annual crop production with grazing of forage crops, cover crops, crop residues, and winter grazing with summer crop production (Kumar et al., 2019). However, region-specific issues have a major impact on how crop-livestock systems can be implemented. For example, in colder climates with a short grazing season, livestock performance is strongly related to winter feed management, which can be a significant cost. Stored forage production (such as hay, haylage, and corn silage) is therefore an integral aspect of crop-livestock integration in these climates (Kumar et al., 2019). Yet, the practice of rotating annual crops such as corn with perennial forage has been limited in the United States, and the costs and benefits of these systems are presently understudied.

Aligning production goals with environmental sustainability is critical to achieving sustainable intensification, and environmental stewardship is one of many factors considered by farmers when making agricultural management decisions, alongside financial limitations which constrain their options (White A. et al., 2021; White et al., 2022a). Agricultural sustainability goals can be achieved alongside environmental sustainability goals through improvements in soil health (Neher et al., 2022). Soil health is defined as the continued capacity of a soil to function as a vital living ecosystem that sustains plants, animals, and humans (USDA-NRCS, 2022). This definition acknowledges the role that biological processes play in influencing dynamic soil properties and soil functions that are foundational to sustainability (Neher et al., 2022). Measures of biological, physical and chemical soil health parameters are now widely used as indicators of ecosystem functions and ecosystem services from changes in farming practices and can help assess the effectiveness of conservation practices in meeting multiple goals (Wall et al., 2012; Abbott and Manning, 2015; Adhikari and Hartemink, 2016; White A. et al., 2021; White A. C. et al., 2021; Neher et al., 2022).

The integration of conservation practices, crop diversification, or crop rotation may help farmers protect against weather-related crop stress and increase crop yield while improving soil health and underlying ecosystem services (Nunes et al., 2018; Page et al., 2020; Yang et al., 2020). For example, practices that increase organic matter can mitigate flood damage through increased water holding capacity (Bhadha et al., 2017), increased aggregate stability can decrease erosion (Barthès and Roose, 2017), soil organic carbon increases can contribute to mitigating climate change (Lal et al., 1999) and cover crops can reduce erosion by providing physical cover (De Baets, et al., 2011). However, the nuances of site conditions, soil texture, and the way conservation practices are implemented influence these outcomes, meaning that both synergies and tradeoffs are possible (Palm et al., 2014; Nunes et al., 2018; Page et al., 2020). Context-specific and usable information tailored to realistic production methods, and relevant information on cropping system modifications and subsequent influence on yield and ecosystem services, are needed in every region of the world to support farmers' decisions.

Corn silage and perennial grass/legume forage cropping systems are prevalent across most dairy producing agricultural areas such as Vermont, United States. For example, corn silage covers 65,560 ha in Vermont, accounting for 13.5% of the agricultural landscape (USDA, 2021). Hay and pasture cover 22.9% (111.290 ha) of the agricultural land (USDA, 2021). Dairy operations feed a mix of annual and perennial forages to meet the dietary requirements of cows, often including a hay, haylage, corn silage, pasture, and various grain concentrates. Conventional management of corn for silage in these systems is characterized as continuous corn planted at a high seeding density. Unlike corn grown for grain, the production of corn silage requires the entire aboveground biomass to be harvested and removed from the field, leaving no crop residue to protect the soil from weather elements through the fall, winter, and spring before the next crop is planted. This can lead to significant soil erosion and declining soil organic matter levels over time (Balík et al., 2020). The sustainable intensification of these annual forage systems has been challenging in Northern New England, primarily a result of a short growing season and difficult landscape. Heavy, cold, and wet soils in the spring encourage spring tillage, providing limited opportunity for adoption of no-till. Rocky and steep slopes limit the land-base available for corn and hay rotations, leading to the best soils being reserved for continuous corn. Silage corn varieties typically require 2,200–2,800 growing degree units (GDUs) to reach maturity and the 30-year average GDD (base 10 °C) in Burlington, Vermont is 2,549 (NOAA, 2022). This means that the time available after harvest to implement conservation practices and establish a cover crop before winter is very limited. In the coming years, variability in precipitation patterns associated with climate change may mean fewer field working days due to wet soil conditions (Tomasek et al., 2017), exacerbating challenges associated with an already short, cold and wet growing season.

In light of these challenges, greater adoption of forage crop rotation, no-till, and cover cropping, may help farmers simultaneously increase soil health, enhance resilience to climate change, and stabilize yields for forage management in integrated livestock systems. Rotation from annual to perennial production systems can increase soil health, and rotating from perennial to annual can give a boost in yields (Stanger and Lauer, 2008; Undersander and Barnett, 2008; Darby et al., 2019). Hay and pasture fields in Vermont have higher soil carbon socks and soil health than corn fields (White et al., 2022b). Extensive research has found that cover cropping increases the overall health of agricultural systems by scavenging excess nutrients (Clark, 2010), increasing water infiltration (Haruna et al., 2018), reducing surface runoff (De Baets, et al., 2011), alleviating compaction pressure (Chen and Weil, 2011), building soil tilth, increasing biodiversity, and building organic matter. Furthermore, cover cropping can help enhance the benefits of other farming practices, such as no-till planting, creating synergies that increase farm financial and environmental sustainability. For example, Sapkota et al. (2012) found that compared to conventional till, no-till systems had 1.12% higher soil organic matter content, 71% more soil microbial biomass, 44% higher soil respiration, greater arthropod abundance, and improved soil structure stability. Long-term no-till corn in the northeastern United States has demonstrated soil health benefits alongside yield increases or maintenance of yields (Nunes et al., 2018).

The goal of this study was therefore to evaluate forage crop yield and quality and soil health metrics in alternative cropping systems that incorporate annual and perennial forage crop rotation, cover crops, and no-tillage, compared to continuous corn silage. We present the results of long-term research on annual production systems in northern New England United States with a novel focus on forage production, which is a critical element of crop-livestock integration in this region. Using a unique 10-year dataset from Borderview Research Farm in Vermont, United States, we evaluate the degree to which these conservation practices and perennial-annual rotations influence dimensions of soil conservation, ecosystem service provisioning and forage production over time. We hypothesize that integrating perennial forage rotations, cover crops, and no till will improve soil health indicators, carbon sequestration, and crop quality and yield in continuous corn production systems, but that temporal tradeoffs and synergies are likely to exist when implementing these practices.

2 Materials and methods

2.1 Study design

Our research draws on data from a long-term replicated plot research trial on corn cropping systems which was established at Borderview Research Farm in Vermont, United States. The experiment was established in 2009. Soil health data was collected alongside yields starting in 2012 and monitored annually until 2021. Forage quality was analyzed starting in 2014 and evaluated annually until 2021.

The experimental design was a randomized complete block with replicated treatments of corn grown in various cropping systems (Table 1). In 2009, there were three treatments each in 6.10 × 15.2 m plots. Four plots were continuous corn (CC 2009) which reflects typical agronomic practices of that time with tillage and no-cover crops. Another four plots were continuous corn with over wintering cover crop (WCCC 2009) which reflects a rotation of continuous tilled corn planted with fall cover crop. There were 12 perennial forage (PF) plots that were planted with a mixture of alfalfa and meadow fescue in 2008. In 2011, a fourth treatment was added when four PF plots were transitioned to no-till corn plots (NT 2011) which reflects continuous corn with no-till practices. The two final treatments (fifth and sixth treatments) are corn-hay rotations with similar management patterns, but in staggered rotation years. In the first rotation (ROTC 2014) four PF plots were transitioned to new corn plots in 2014, and then seeded into PF again in 2020. The second rotation treatment (ROTC 2020) was in PF until it was rotated into corn in 2020. Additionally, in the fall of 2020 the NT plots were split (6.05 × 15.2 m) to maintain NT plots and introduce plots with combined no-till and cover crop practices which will benefit future research.

2.1.1 Site description

This research takes place in Alburgh, VT (long. 45.009072, lat. −73.307,830) on Amenia silt loam soil (loam skective, mesic, Lithic Eutrudepts). According to the Köppen climate classification system, this region is "humid continental mild summer, wet all year" (Dfb) (PlantMaps, 2022). The 30-year average temperature is 8.22 °C with a 30-year average of 2,625 growing degree days (base 10.0 °C). The 30-year average precipitation amount is 95.0 cm with an additional 216 cm of snow (base 10.0 °C) (NOAA, 2022). The average 30-year winter temperature (December-February) is −4.94 °C (NOAA, 2022).

2.1.2 Field practices

The CC 2009, WCCC 2009, ROTC 2014, and ROTC2020 plots were tilled between 6-May and 16-May with Pottinger Terra Disc (Valparaiso, IN) at 20–25 cm depth for field bed preparation and weed control when in corn. Corn was planted between 7-May and 25-May at an average rate of 84,000 seeds hectare^{-1} in 76 cm rows with a John Deere 1750 corn planter (Moline, IL). In 2018, a planter malfunction resulted in a seeding rate of 42,000 seeds ha^{-1}. Silage varieties varied over the years with an average relative maturity

TABLE 1 Corn cropping system treatments evaluated for yield, forage quality and soil health in this study.

Crop	Management method	Treatment abbreviation
Corn silage	Continuous corn, tilled	CC2009
Corn silage	Winter cover crop, tilled	WCCC2009
Corn silage	No-till corn, established into PF plots in 2011	NT2011
Corn silage	No-till corn with cover crops, established in 2020 within plots that had been in no-till since 2011	NTCC2020
Corn silage & Perennial Forage	Perennial forage, rotated into continuous corn in 2014, and then rotated back to perennial forage in 2020	ROTC2014
Corn silage & Perennial Forage	Perennial forage, rotated into continuous corn in 2020	ROTC2020

(RM) of 94, minimum of 86 and maximum of 105. Typical corn starter was applied 4, 8, 8 kg ha^{-1} of nitrogen N), phosphorus P), and potassium K), respectively. Corn was side-dressed according to the highest nitrate soil test result which was an average of 125 kg ha^{-1} N when corn was in the V4 stage (between 17-Jun and 5-Jul). Winter cover crop was typically planted in late September with cereal rye (*Secale cereale*) at a rate of 110 kg ha^{-1}. Cover crops were terminated in NTCC2020 plots with herbicide before corn planting. For early season weed control, herbicide was applied between 14-May and 5-Jun. Later season weed control was achieved through spot spraying with systemic herbicides. Corn was typically harvested between 3-Sep and 18 September It should be noted that in 2020, corn in the ROTC2020 plots was planted after first cut of PF and thus with a later planting date, matured later and had a later harvest date (29-Sep) than any of the other corn plots which were harvested on 3-Sep).

The PF (perennial forage) plots were established with 16.0 kg ha^{-1} mixture of 30% alfalfa and 70% tall fescue. On 6-May 2020, PF in the ROTC2014 plots was established with 22.5 kg ha^{-1} mixture of 60% alfalfa and 40% tall fescue. Typically, forage plots were fertilized with an application of 4, 8, 8 kg ha^{-1} of N, P, and K, respectively after first cut and 60.5 kg ha^{-1} K after second cut. With the exception of a rotation year into corn where only first cut was taken (ROTC 2020) or rotation into perennial forage (ROTC 2014) when harvest occurred only twice during the first 2 years to encourage establishment of the new forage seeding. Perennial forage plots were harvested three times a year between late May and mid-September.

2.1.3 Sampling and analysis procedures

Indicators of soil health were measured annually. Numerous approaches to assessment of soil health have been developed that move beyond chemical analyses to include biological and physical indicators as well. Our study used the widely adopted Comprehensive Assessment of Soil Health developed by Cornell University's Soil Health Lab to measure a suite of biological, chemical and physical indicators of soil health (Meobius-Clune et al., 2016). Soil samples were collected from each plot between 26-April and 15-May annually from 2012 to 2021 using the methods described in Moebius-Clune et al. (2016). Composite soil samples were then submitted to the Cornell Soil Health Laboratory for the Comprehensive Assessment of Soil Health (CASH) analysis (Ithaca, NY).

Percent aggregate stability was measured by Cornell Sprinkle Infiltrometer and indicates ability of soil to resist erosion. Predicted percent available water capacity and predicted soil protein (N mg/soil g) was calculated with a Random Forest model from a suite of measured parameters and soil texture (van Es et al., 2019). Percent organic matter was measured by loss on ignition when soils are dried at 105 °C to remove water then ashed for two hours at 500 °C (CASH adaptation from Broadbent, 1965). Total nitrogen is measured with DUMAS combustion methodology. It measured organic (living and non-living) and inorganic (mineral) forms of nitrogen. Active carbon (active C mg/soil kg) was measured with potassium permanganate and is used as an indicator of available carbon (i.e., food source) for the microbial community. Soil respiration (CO_2 mg/soil g) is measured by amount of CO_2 released over a four-day incubation period and is used to quantify metabolic activity of the soil microbial community (Zibilske, 1994).

Corn silage was harvested with a John Deere 2-row chopper (Moline, IL) and yields weighed in a wagon fitted with scales. Perennial forage was harvested and weighed with a Carter Forage Harvester (Brookston, IN) fitted with scales in one 0.914-m x 15.2-m strips. Dry matter yields were calculated with an approximate two-pound subsample of the harvested material from each strip was collected, weighed, dried and reweighed.

Forage quality was analyzed using the FOSS NIRS (near infrared reflectance spectroscopy) DS2500 Feed and Forage analyzer. Dried and coarsely-ground plot samples were brought to the UVM's Cereal Grain Testing Laboratory where they were reground using a cyclone sample mill (1 mm screen) from the UDY Corporation. The samples were then analyzed using the FOSS NIRS DS2500 for crude protein (CP), neutral detergent fiber (NDF), and neutral detergent fiber digestibility in 30 h (NDFD30).

2.1.4 Weather data

Monthly total precipitation records for 2012 through 2021 from the weather station in Burlington Vermont, United States were obtained from the NOAA National Weather Service. Precipitation levels for months prior to sampling were summed and plotted to assess relationships with soil health measurements.

2.1.5 Interpretation as ecosystem services

Ecosystem services provide a framework for assessing sustainability of socially relevant ecological outcomes and processes. It is recommended that indicators of ecosystem services be easily measured, sensitive to changes in the system and capture the connection between biophysical changes and socially relevant outcomes (Dale and Polasky, 2007; Olander et al., 2018). In this study we drew from prior work by Neher et al. (2022), Dube et al., 2022, White A. et al. (2021) and White A. C. et al. (2021) to interpret benefit-relevant soil health parameters as ecosystem services. Supporting ecosystem services are defined as those that underpin other ecosystem functions and services (Dominati, 2013). Measures of respiration and active carbon directly reflect the microbial, metabolic, and nutrient cycling activity in the soil that underpin other soil functions and ecosystem services (Meobius-Clune et al., 2016), and are thus interpreted as indicators of soil health supporting ecosystem services. Regulating ecosystem services are the benefits obtained from regulation of ecosystem processes, including climate regulation, water regulation, erosion control, and more (Leemans and De Groot, 2003). In our study, aggregate stability was measured using a simulated rainfall-based test (Meobius-Clune et al., 2016), and is interpreted as a direct indicator of soil conservation and resilience to extreme precipitation (White A. et al., 2021). Soil organic matter content is a direct measure of the dynamic portion of soil carbon content, and net changes in organic carbon content over time is interpreted as an indicator of climate regulation services through carbon storage and sequestration (Dube et al., 2022). Available water capacity is a direct measure of plant available water in soil and was interpreted as an indicator of drought resilience (White A. et al., 2021). Finally, we interpret both yield and forage quality as indicators of impacts of food provisioning services. Identifying ecosystem services in this way is a useful lens to highlight the socially relevant aspects of natural resources and ecosystem functions. In the presentation of results, we bring focus to significant influences and directionality of impact on ecosystem services as in White A. et al. (2021).

2.2 Statistical analysis

We used linear mixed models with repeated measures to evaluate the influence of time and treatment on soil health and yields. This analysis was followed by ANOVA and prediction of treatment means to support our interpretation, inference and conclusions (Gezan and Carvalho, 2018). In addition to evaluating a dependent variable of each metric as observed, we also detrended the data by calculating the 'deviation from continuous corn' for each observation, taking the difference between that observation and the mean value for the continuous corn plots in that year. This removed the effects of interannual variability and allowed our analysis to focus on the way the treatments differ from conventional practices (continuous corn). For example, when analyzing aggregate stability, we ran our statistical analysis methods on aggregate stability as measured, as well as the deviation in aggregate stability from continuous corn each year.

2.2.1 Model specifications

We fit linear mixed models in *R* (Rstudio Team, 2022) using the *lme4* package (Bates et al., 2015) to identify the influence of time and treatment on soil health characteristics, yields and forage quality. Treatment, year and block were considered fixed effects. Plot was considered a random effect. Interaction terms between year and treatment, block and plot were considered. The model was refined to include only interactions between year and treatment, by stepwise removal of non-significant terms, to optimize Akaike's Information Criterion (AIC), resulting in a best fit model as follows:

$$y = \mu + Yr + Trt + Trt \times Yr + Blk + Pl$$

Where *Yr* is the year, *Trt* is the treatment, *Trt xYr* is the interaction between year and treatment, *Blk* is the block, and *Pl* is the plot as a random effect. ANOVA (Type II Wald F tests with Kenward-Roger df) was then conducted on model results using the *car* package in *R* (Fox and Weisberg, 2019). Effects were considered significant at a level of $p = 0.05$. Where significant impacts among treatments were identified, comparisons of means were conducted.

2.2.2 Post hoc tests

To support interpretation of the mixed model analysis, we conducted mean comparison tests where significant influences were identified. For variables with significant time:treatment interactions we ran Holm corrected pairwise *t*-test comparisons with the continuous corn treatment over time. A p-level of 0.05 was used to determine significant differences between treatments. These *post hoc* tests are considered secondary and supplemental to the model-based analysis.

3 Results

3.1 Summary

Our observations identified significant temporal, treatment and time:treatment interactions that influenced soil and yield characteristics. Treatments evaluated in our study significantly influenced soil health characteristics, total dry matter yield, and CP and NDF in comparison to continuous corn, but did not significantly influence corn yields, NDF30 or soil available water capacity (Table 2; Table 3). In treatments which rotated corn with perennial forages, overall DM yield was less than in continuous corn, but only significantly less in the ROTC2020 treatment (Table 4). Significant time:treatment interactions indicate that the impact of corn cropping systems on soil health and yield are complex, dynamic, and can be variably affected by management practices. Details of the temporal influence on significant relationships among treatments is supported by secondary analysis in Tables 5 and Table 6.

3.2 Soil health

3.2.1 Aggregate stability

Aggregate stability was significantly influenced by time ($p < 0.001$), treatments ($p < 0.001$), and interactions between time and treatments ($p < 0.001$) (Table 2). Model outputs indicate deviation in aggregate stability from CC was significantly increased by NTCC ($p < 0.001$), NT ($p = 0.034$), ROTC 2014 ($p < 0.001$), and ROTC 2020 ($p < 0.001$), but not the WCCC treatment. Significant interactions between time and NT, ROTC 2014, and ROT2020 treatments is reflected in the model output

TABLE 2 Significant influences on soil health parameters; ANOVA *p*-values and Marginal R2 values of repeated measures linear mixed models of soil health parameters, and the deviance of soil health parameters from continuous corn (CC).

Soil health indicators	Year	Treatment	Block	Treatment:Year interaction	Marginal R^2
Aggregate stability	**	***	0.483	***	0.658
Difference in aggregate stability from CC	***	***	0.489	***	0.817
SOM	***	***	***	**	0.655
Difference in SOM from CC	*	***	***	***	0.699
Available water capacity	***	0.364	0.992	0.86	0.232
Difference in available water capacity from CC	0.623	0.427	0.943	0.567	0.107
Surface hardness	***	*	0.511	0.123	0.509
Difference in surface hardness from CC	***	***	0.173	**	0.330
Subsurface hardness	***	0.458	0.27	0.719	0.394
Difference in subsurface hardness from CC	0.595	*	*	0.13	0.166
Active carbon	***	*	*	0.187	0.242
Difference in active carbon from CC	0.346	**	*	**	0.320
Respiration	**	***	0.156	***	0.686
Difference in respiration from CC	0.553	***	0.167	***	0.734
*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '' 1*					

TABLE 3 Significant influences on yields and forage quality; ANOVA *p*-values and Marginal R2 values of repeated measures linear mixed models of corn yield (35% DM), dry matter yield for corn and forage, and forage quality, as well as the deviance in those metrics from continuous corn (CC).

Yield and quality parameters	Year	Treatment	Block	Treatment:Year interaction	Marginal R^2
Corn yield (35% DM)	*	0.213	0.614	0.694	0.122
Difference in corn yield from CC	0.818	0.217	0.633	0.602	0.133
DM yield (perennial and annual)	0.14	***	0.840	*	0.249
Difference in DM yield from CC	0.09	***	0.704	**	0.359
Crude protein	***	***	0.726	***	0.657
Difference in crude protein from CC	0.498	***	0.706	***	0.665
Neutral detergent fiber content (NDF)	***	***	1.0	***	0.495
Difference in NDF from CC	0.335	***	0.993	***	0.472
Neutral detergent fiber content at 30 h (NDFD30)	0.219	0.260	1.0	0.953	0.051
Difference in NDFD30 from CC	0.693	0.289	0.999	0.871	0.051
*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '' 1*					

(Supplementary Material S3). The difference in aggregate stability between the ROTC2014 and CC was 23% at the start of the study (2012), and the difference declined after the ROTC2014 rotated into corn in 2014, getting to 9.43% in 2020 (Figure 1, Supplementary Material S2). In the ROTC 2020, aggregate stability relative to CC increased over time, starting at 19.7% more aggregate stability in 2012, and ending at 45.7% more than continuous corn in 2014.

3.2.2 Available water capacity

Treatments had no effect on available water capacity. Available water capacity was significantly influenced only by year (p < 0.001) across the study, but the deviation in available water capacity from continuous corn was not significantly influenced by time. Block (p < 0.05) was the only significant influence on the way AWC deviated from continuous corn.

TABLE 4 Significant influences on ecosystem service provisioning by treatment compared to continuous corn (CC). This is based on the repeated measure mixed model that incorporates that influences of treatments, time and time:treatment interactions from 2012 to 2021. The "–" symbol is a negative impact, the "+" symbol is a positive impact, the "~" symbol indicates is is not significant, and " –/+" indicates a variable impact depending on year.

Ecosystem service	Indicator	Treatment				
		NT	NTCC	WCCC	ROTC2014	ROTC2020
Climate regulation through carbon storage	Soil organic matter (%)	~	+	~	+	~
Soil health supporting services	Active carbon (ppm)	~	~	~	–/+	~
	Respiration (mg CO_2 g^{-1} dry weight)	~	+	~	~	+
Soil conservation	Aggregate stability (%)	+	+	~	+	+
Resilience to extreme precipitation	Aggregate stability (%)	+	+	~	+	+
Drought resilience	Available water capacity (g g^{-1})	~	~	~	~	~
Food provisioning	Corn yield (35% DM)	~	~	~	~	~
	Dry matter yield, annual and perennial (kg $hectare^{-1}$)	~	~	~	~	–
	Crude protein (% DM)	~	~	~	+	+
	NDF (% DM)	~	~	~	~	–
	NDF30 (% NDF)	~	~	~	~	~

Among the treatment abbreviations; NT, is no till; NTCC, is no till and winter cover crop; WCCC, is winter cover crop, ROTC2014 is 2 years hay-6, years corn-2 years hay, and ROTC2020 is 7 years hay-3, years corn.

3.2.3 Surface and subsurface hardness

Subsurface hardness was significantly influenced by year ($p < 0.001$) only, yet the detrended data shows that the deviation in subsurface hardness from that of continuous corn was significantly influenced by treatment ($p < 0.001$), and block ($p < 0.01$). The deviation in surface hardness from that of continuous corn was significantly influenced by year ($p < 0.001$), treatment ($p < 0.001$), and an interaction between year and treatment ($p < 0.001$) (Table 2). Deviation in surface hardness from continuous corn was significantly influenced by the ROTC2014 treatment ($p < 0.001$) and the WCCC treatment ($p = 0.045$). Significant interactions between time and the ROTC2014 and WCCC treatments were also observed (Supplementary Material S3). In the ROTC2014 treatment, surface hardness was 69 psi greater than continuous corn treatment at the start of the data collection when the rotation was in perennial forages. Following the rotation into corn, surface hardness in the ROTC2014 treatment became more similar to surface hardness in the continuous corn plot. The average difference from continuous corn was 40.6 psi in 2014, 8.12 psi in 2015, and -36 psi in 2016 (Figure 1, Supplementary Material S2). The WCCC treatment experienced a similar trend (Figure 1), starting at 20.5 psi greater than continuous corn in 2012, dropping to 27.75 psi less than continuous corn in 2016, and ending at 12 psi less than continuous corn in 2021. These trends track with the antecedent moisture conditions during sampling time plotted, alongside surface hardness in Figure 2.

3.2.4 Organic matter

Soil organic matter was significantly influenced by time ($p < 0.01$), treatment ($p < 0.001$), block ($p < 0.001$) and interactions between time and treatment ($p < 0.001$) (Table 2). Model outputs indicate that the deviation in organic matter content from CC was significantly increased by the NTCC treatment ($p = 0.019$) and the ROTC2014 treatment ($p < 0.001$). A significant interaction between time and the ROTC2014 treatment was observed (Supplementary Material S3). In 2021, the NTCC treatment had 0.26% more organic matter than the CC treatment (Supplementary Material S2). In 2013, the ROTC2014 treatment had 1.26% more soil organic matter than the CC treatment, and this difference declined annually after it was transitioned to corn in 2014, and 6 years later, in 2019, the ROTC2014 treatment had only 0.19% more organic matter. Following return to perennial forages, the organic matter levels increased slightly to 0.26% greater than the CC treatment (Figure 3, Supplementary Material S2). Organic matter levels were highest in ROTC2020 in all years, but not captured as significant in the model.

3.2.5 Active carbon

Active carbon was significantly influenced by year ($p < 0.001$), treatment ($p < 0.001$), and block ($p < 0.001$) (Table 2). The deviation in active carbon from that of CC was significantly influenced by treatment ($p < 0.001$) and the interaction of treatment and year ($p < 0.001$). Deviation in active carbon from CC was significantly influenced by the ROTC2014 treatment, and the interaction of time with the ROTC2014 treatment (Supplementary Material S3). Our results indicate that active carbon levels were both positively and negatively influenced by the rotation. Active carbon levels were 118 ppm greater in ROTC2014 than CC in 2013, and this difference was reduced over time when the rotation was planted with corn. In 2020, the ROTC2014 treatment had 5.36 ppm active carbon less than the CC treatment, and after it was rotated into perennial forage again the active carbon levels increased to 40 ppm greater than the CC treatment (Figure 3, Supplementary Material S2).

TABLE 5 Significance level of *post hoc* Holm corrected pairwise *t*-test comparisons with continuous corn treatment over time for soil variables with significant time: treatment interactions. NA is no data for that year, ns is not significant, * is significant to 0.05, ** is significant to 0.01, and * is significant to 0.001 or less. Mean values over the entire timeframe are in the farm right column.**

Treatment	Significant difference from continuous corn by year										Mean
	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	
Aggregate stability											**(%)**
NTCC2020	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	**	24.8
NT2011	*	ns	ns	ns	**	**	ns	**	**	ns	24.0
ROTC2014	*	ns	ns	ns	ns	ns	ns	ns	ns	ns	16.3
ROTC2020	*	ns	ns	**	*	*	*	***	**	**	32.7
WCCC2009	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	3.4
Organic matter											**(%)**
NTCC2020	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	ns	0.26
NT2011	ns	ns	ns	ns	ns	ns	ns	ns	ns	**	0.30
ROTC2014	ns	ns	**	ns	ns	ns	ns	ns	ns	ns	0.42
ROTC2020	ns	*	ns	ns	ns	ns	ns	ns	*	ns	0.88
WCCC2009	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	0.00
Surface hardness											(psi)
NTCC2020	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	ns	−6.00
NT2011	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	24.87
ROTC2014	ns	ns	ns	ns	*	ns	ns	ns	ns	ns	13.26
ROTC2020	ns	ns	ns	ns	ns	**	ns	*	ns	ns	42.66
WCCC2009	ns	*	ns	ns	ns	ns	ns	ns	ns	ns	10.47
Active carbon											(ppm)
NTCC2020	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	ns	−13.2
NT2011	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	21.9
ROTC2014	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	19.2
ROTC2020	ns	ns	ns	ns	ns	ns	ns	ns	*	ns	74.6
WCCC2009	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	−16.7
Respiration											(CO_2 mg/g)
NTCC2020	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	ns	0.16
NT2011	*NA*	*NA*	ns	*	ns	ns	*	ns	ns	ns	0.11
ROTC2014	*NA*	*NA*	**	ns	ns	ns	ns	ns	ns	ns	0.13
ROTC2020	*NA*	*NA*	ns	*	**	*	ns	ns	ns	**	0.40
WCCC2009	*NA*	*NA*	ns	ns	ns	ns	ns	ns	ns	ns	0.06

3.2.6 Respiration

Respiration was significantly influenced by year ($p < 0.01$), treatment ($p < 0.001$), and an interaction between treatment and time ($p < 0.001$). The difference in respiration between treatments and CC was influenced by treatment ($p < 0.001$) and an interaction between treatment and time ($p < 0.001$) (Table 2). The deviation from CC in respiration was significantly increased by the NTCC and ROTC2020 treatments, and the interaction of time with the ROTC2020 treatment (Supplementary Material S3).

3.3 Yields and forage quality

3.3.1 Corn yield

Corn yields were significantly influenced only by year ($p < 0.01$) (Table 3). The difference in yield from continuous corn was not significantly influenced by any treatment. This was not calculated for rotation treatments in years when they did not harvest corn, so overall dry matter yields (next section) are a more appropriate comparison.

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TABLE 6 Significance level of *post hoc* Holm corrected pairwise *t*-test comparisons with continuous corn treatment over time for yield variables with significant time:treatment interactions. NA is no data for that year, ns is not significant, * is significant to 0.05, ** is significant to 0.01, and *** is significant to 0.001 or less. Mean values over the entire timeframe are in the farm right column.

Treatment	Significant difference from continuous corn by year										Mean
	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	
Dry matter											(Yield at 35% dry kg ha^{-1})
NTCC2020	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	ns	0.49
NT2011	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	−0.43
ROTC2014	ns	**	ns	ns	ns	ns	ns	ns	*	ns	−0.90
ROTC2020	*	*	ns	*	*	*	ns	**	ns	ns	−2.7
WCCC2009	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	0.41
Crude protein											(Standardized dm/ha)
NTCC2020	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	ns	0.88
NT2011	*NA*	*NA*	ns	ns	ns	ns	ns	ns	ns	ns	0.18
ROTC2014	*NA*	*NA*	ns	ns	ns	ns	ns	ns	***	**	23.98
ROTC2020	*NA*	*NA*	**	*	**	***	**	**	ns	ns	70.07
WCCC2009	*NA*	*NA*	ns	ns	ns	ns	ns	ns	ns	ns	−0.76
NDF											(% of DM)
NTCC2020	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	ns	−9.95
NT2011	*NA*	*NA*	ns	ns	ns	ns	ns	ns	ns	ns	−2.34
ROTC2014	*NA*	*NA*	ns	ns	ns	ns	ns	ns	***	ns	25.35
ROTC2020	*NA*	*NA*	*	ns	*	*	ns	ns	ns	ns	103.30
WCCC2009	*NA*	*NA*	ns	ns	ns	ns	ns	ns	ns	ns	−4.07

3.3.2 Dry matter yields

The difference in dry matter (DM) yield from continuous corn was significantly influenced by treatment ($p < 0.001$) and the interaction of treatments over time ($p < 0.001$) (Table 3). The model results indicate that only the ROTC2020 treatment significantly influenced the difference in DM yields from continuous corn (Supplementary Material S3). While in perennial forage, the ROTC2020 treatment yielded between 1,793 kg ha^{-1} and 11,591 kg ha^{-1} less than the continuous corn treatment, and was significantly less in most years (Table 6). In 2020, the year that rotation returned to corn, it yielded 314 kg ha^{-1} of dry matter more than the CC treatment. The DM yield differentials were greatest in years when the rotation was planted with perennial forages (Figure 4). Cumulative DM yields over the 10 years of this study were greatest in the WCCC treatment, followed by CC, then NT, ROTC 2014, and then ROTC 2020 (Figure 5).

3.3.3 Crude protein

Treatments and the interaction of treatments with time significantly influence the deviation of CP from CC ($p < 0.001$) (Table 3). Model results indicate that the ROTC2014 and ROTC2020 treatments significantly influenced differences in CP from continuous corn. In years when perennial forage was harvested from these treatments, CP levels were significantly greater, at levels between 63 and 122 g kg^{-1} more than CC treatment means (Figure 6; Table 6, Supplementary material S2).

3.3.4 NDF

The deviation from continuous corn in NDF concentrations was significantly influenced by treatments and the interaction of treatments with time ($p < 0.001$) (Table 3). Model results indicate the ROTC2020 treatment significantly influenced differences in NDF. The ROTC2020 had higher NDF values indicating that it was lower quality and could potentially limit dry matter intake of livestock. Post hoc comparison of means show the ROTC2020 treatment was significantly higher in 2014, 2016 and 2017, years when it was in hay (Table 6). Similarly, the ROTC2014 was significantly higher in 2020, a year when it was planted in hay (Table 6).

3.3.5 NDF30

Significant influences on NDFD30were not observed in this study (Table 3).

3.4 Ecosystem services

Here we interpret each treatment's influence on ecosystem service provisioning through the indicators monitored in this

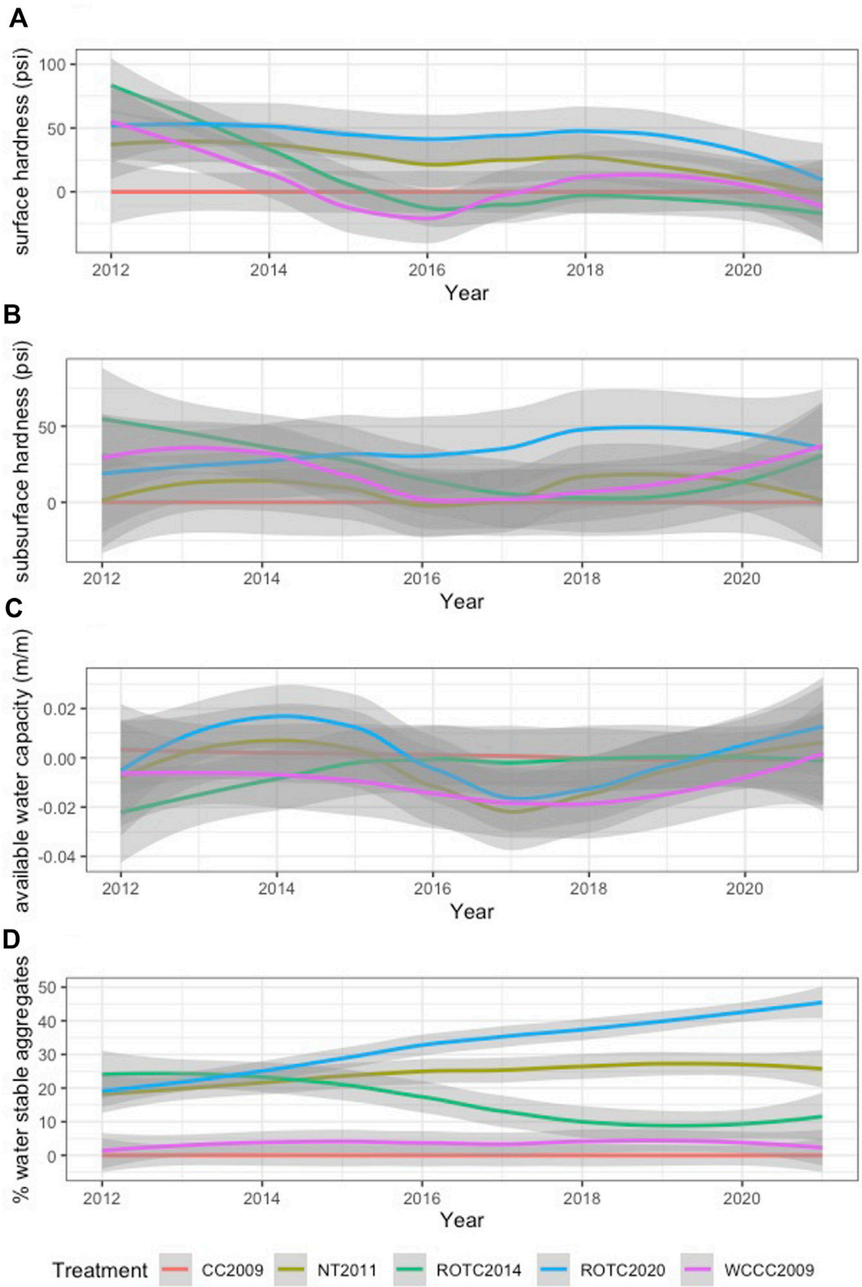

FIGURE 1
Loess plots (locally weighted smoothing) show deviation in soil physical characteristics from continuous corn by treatment from 2012 to 2021: **(A)** Surface hardness **(B)** Subsurface hardness **(C)** Available water capacity **(D)** Aggregate stability.

study (Table 4). The NT treatment was associated with significant improvements in aggregate stability compared to continuous corn, and therefore enhanced soil conservation and resilience to extreme precipitation ecosystem services relative to continuous corn. The WCCC treatment was not significantly associated with any changes in ecosystem services provisioning in this experiment. The NTCC treatment enhanced climate regulation through carbon storage, soil health, soil conservation and resilience to extreme precipitation ecosystem services through increases in soil organic matter, respiration and aggregate stability relative to continuous corn.

The two rotation treatments also influenced indicators of food provisioning. The ROTC2014 treatment increased soil organic matter, aggregate stability and crude protein in comparison to continuous corn but reduced active carbon. This means that the ROTC2014 treatment enhanced climate regulation through carbon storage, soil conservation, resilience

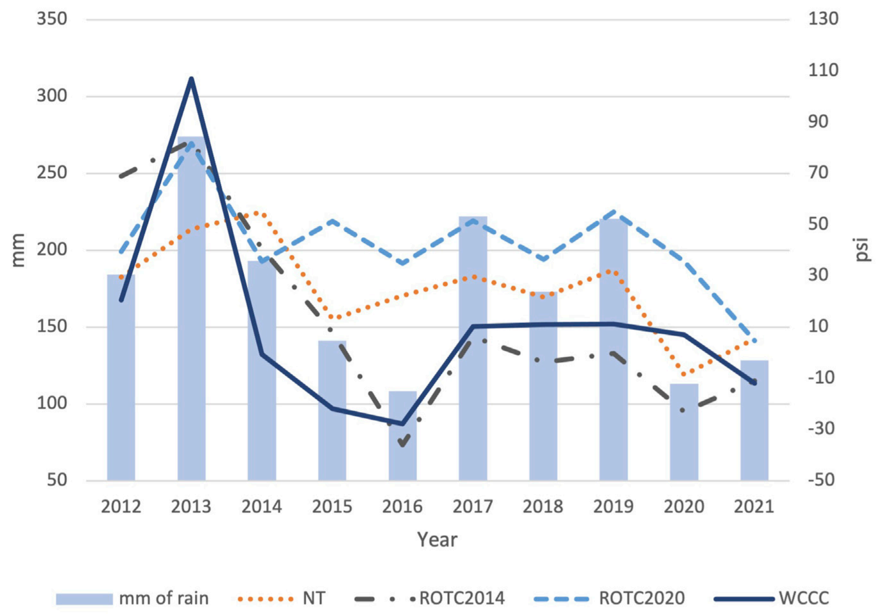

FIGURE 2
Antecedent moisture condition during spring soil sample collection and surface hardness measurements by year. Antecedent moisture condition is total precipitation in April and May months for each year recorded at Burlington International Airport weather station in VT, United States.

to extreme precipitation, and food provisioning ecosystem services, but reduced one aspect of soil health supporting ecosystem services. The ROTC2020 treatment enhanced respiration, aggregate stability, crude protein and NDF relative to continuous corn, but reduced DM yields. This means that the ROTC2020 treatment enhanced soil health, soil conservation, and resilience to extreme precipitation, but had mixed impacts on indicators of food provisioning, where protein content was enhanced but overall DM yields and digestibility was reduced.

4 Discussion

We used a mixed model analysis of variance approach to evaluate the influence of conservation practices and perennial forage rotations on soil health indicators, yields and forage quality over 10 years. Our analysis method centers on the way alternative practices deviate from the performance of continuous corn, and our results indicate that conservation practices and rotations can be implemented to sustain yields while also enhancing aspects of soil health in temperate northern climates similar to Vermont, United States. This is evidence that corn cropping systems can enhance climate regulation, climate resilience, soil health, soil conservation, and food provisioning services through alternative management to continuous corn, however careful consideration of rotation timings and practices in combination is necessary to achieve this potential. The quantification of these benefits as ecosystem services is valuable to informing the effectiveness and impact of conservation programs. Importantly, in the absence of significant increases in yields over conventional management of continuous corn silage, the benefits of the management practices we evaluated accrue primarily to the environment and society, not the farm. Although farmers in Vermont have a strong stewardship ethic towards soil conservation and ecosystem services, their capability to prioritize and invest in these broader public benefits is limited by their financial capacity (White et al., 2022a). Thus, our research implies that conservation incentive and cost-share programs are critical to enabling farms to incur the additional expenses associated with adoption of these identified practices that provide ecosystem services to public beneficiaries. Foremost, our research suggests that no-till in combination with cover cropping in corn silage fields, and a rotation of 4 years of hay to 6 years of corn are likely to achieve the greatest overall benefits in forage production systems.

4.1 Influence of treatments on dimensions of soil health

In many ways, our results confirm that conservation practices and rotations can enhance some aspects of soil health (i.e., Bottinelli et al., 2017; Sharma et al., 2012; Sharma et al., 2018; VandenBygaart, et al., 2003; Wulanningtyas et al., 2021; Nunes et al., 2018). These soil health enhancements are often associated with sustaining corn yields (Kane, et al., 2021) and forage quality. However, various meta-studies examine research that indicates neutral or negative impacts of conservation practices on soil health, crop yield, or crop quality are possible, and that these outcomes may be influenced by weather, soil type, and other management practices (Marcillo and Miguez, 2017; Lu, 2020; Miner, et al., 2020). Our study joins the growing body of research detailing complexity and tradeoffs associated with the outcomes of conservation practices and the multifaceted reality of soil health. Within the physical soil health characteristics, aggregate stability was positively influenced by some of the conservation practices and lowest in the continuous corn

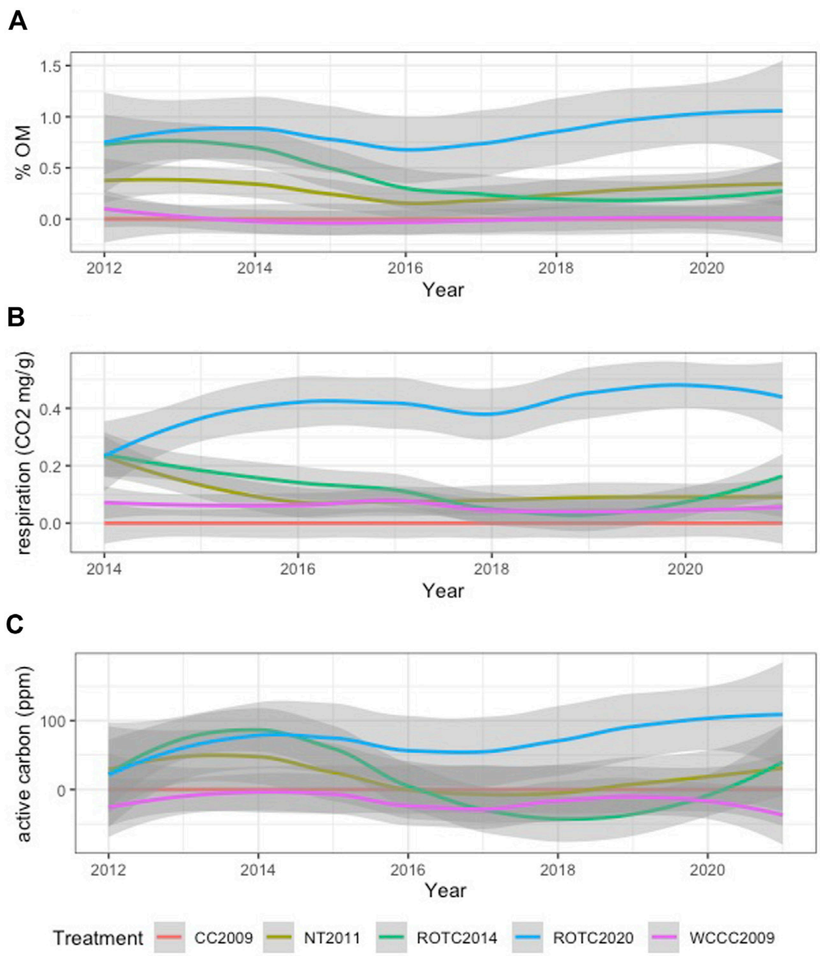

FIGURE 3
Loess plots (locally weighted smoothing) show deviation in soil biological parameters from continuous corn by treatment from 2012 to 2021: **(A)** Soil organic matter content **(B)** Respiration **(C)** Active carbon.

treatment, whereas surface and subsurface hardness were best in the continuous corn treatment and no significant impact on available water capacity was observed.

Surface hardness was significantly influenced by year, treatment and a year:treatment interaction in our study. Mean surface hardness across the 10-year study was between 10 and 42 psi greater in the no-till, rotation and cover crop treatments than continuous corn (Table 5). Although we expected to see improvements in surface hardness from tillage reduction and surface cover, this pattern likely reflects the effect of annual tillage in the continuous corn plots, which loosens the top layer of soil. Our study evaluates corn silage forage systems, which removes all aboveground plant biomass during harvest, leaving little crop residue post-harvest. Although some treatments eliminate tillage, there is no added organic matter to help protect the top layer of soil. If there were manure additions or crop residues, those might provide protection to the top layer of soil minimizing compaction from rainfall and equipment. Precipitation patterns likely also play a role in this observed pattern. We used total precipitation in months of April and May at our study site to approximate antecedent soil moisture levels and rainfall impact on the soil surface prior to sampling (Figure 2) and in years that had more spring rainfall conditions conservation treatments showed greater surface hardness, and an opposite pattern in drier spring seasons.

Increases in tillage have been shown to reduce penetrometer resistance (Mochizuki et al., 2007) and although some research posits that compaction may be alleviated by earthworms and biological processes (Yvan et al., 2012), long term research has shown reduced tillage to increase compaction without evidence of plow pan recovery after 25 years (Schlüter et al., 2018) In our study, subsurface hardness was lowest in the continuous corn treatment. Subsurface hardness was measured with a penetrometer and was highest in plots with perennial or winter roots. It is likely that the dense perennial roots, and even winter cover crop roots, provided resistance to the tool. In future research, bulk density may be a more accurate measure to capture the changes in physical soil characteristics that reflect compaction. The mean winter cover crop treatment was 20.8 psi greater than the continuous corn treatment, and the corn-hay rotation treatments had mean value of 23.5 and 34.5 psi greater than continuous corn. Although the trends for this metric were weak in our study (Figure 1) the potential

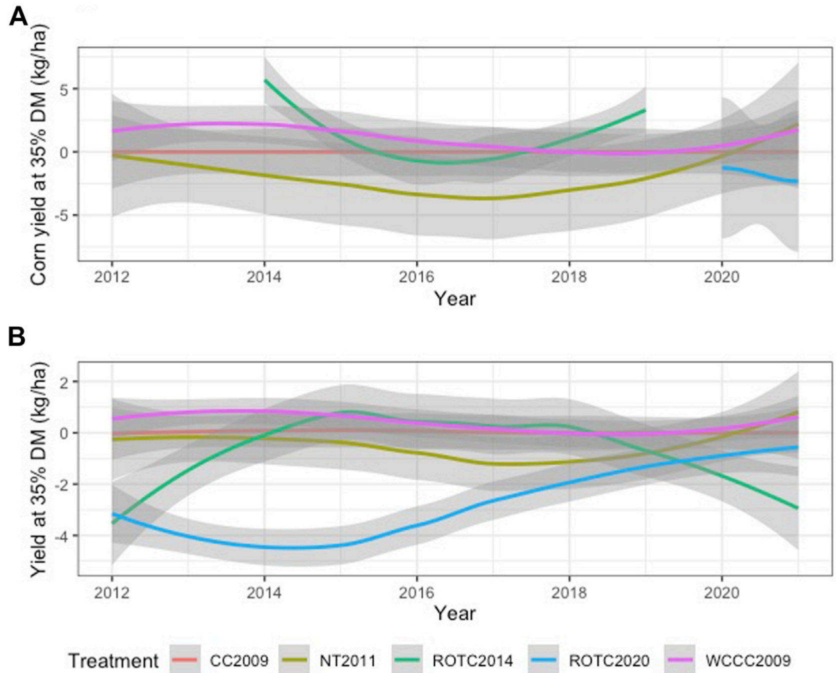

FIGURE 4
Loess plots (locally weighted smoothing) show deviation in **(A)** corn yield and **(B)** dry matter from continuous corn by treatment from 2012 to 2021.

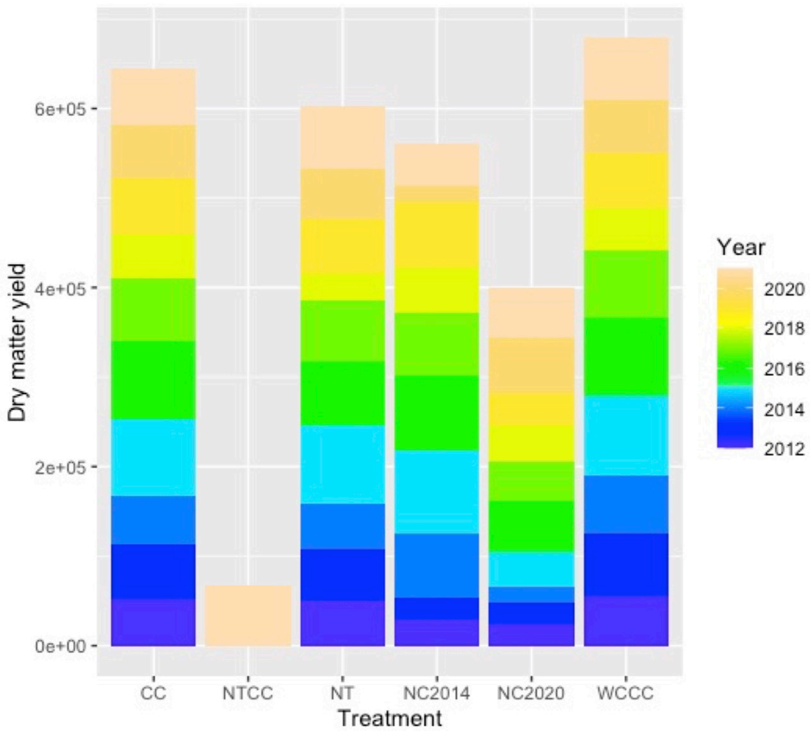

FIGURE 5
Total dry matter yields over the duration of the study by treatment, including dry matter in perennial forage and corn yields.

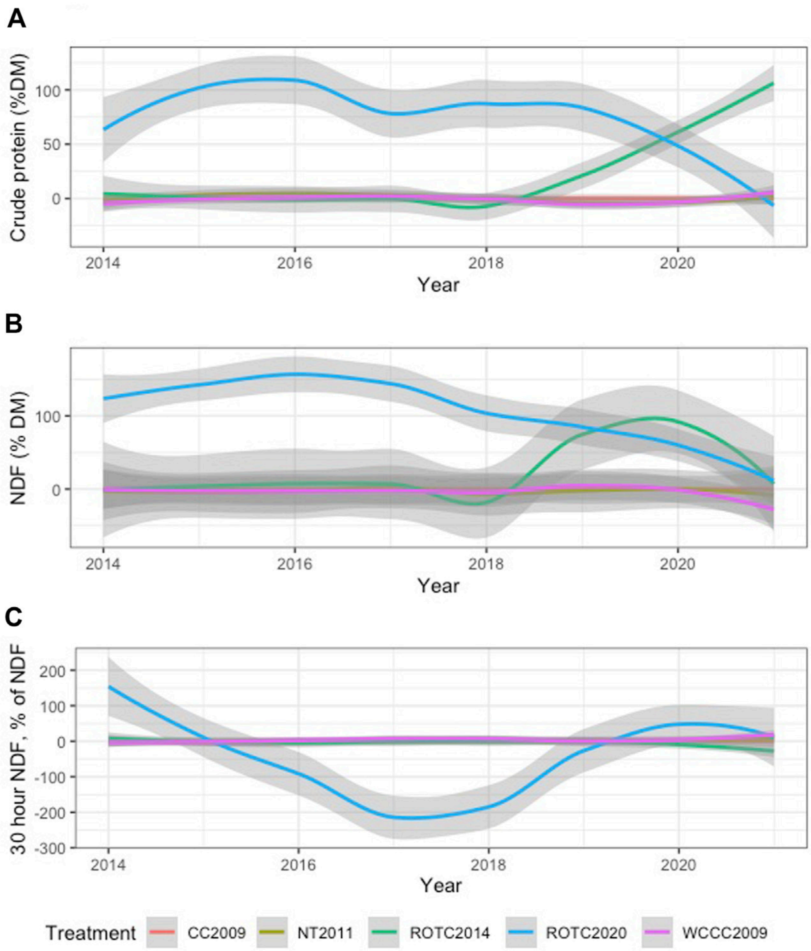

FIGURE 6
Loess plots (locally weighted smoothing) show deviation in forage quality parameters from continuous corn by treatment from 2012 to 2021: **(A)** Crude protein **(B)** NDF **(C)** NDF30.

compaction trade-offs associated with reduced tillage are important to consider in this region, as compaction may restrict root growth and lower yields in the long term.

Cover cropping with winter rye alone had no significant influence on any soil health metrics over a 10-year period of time when compared to continuous corn. This differs from previous research that suggests that cover crops can increase aggregate stability (Ruiz-Comenero et al., 2010). Similarly, although cover crops can supply additions of organic matter, many studies do not correlate cover crops with an increase in soil organic matter (Clark, 2010). This suggests that winter rye cover alone is not sufficient to achieving the respiration or organic matter increases expected based on other research, and highlights that variations on cover crop implementation and management are important to achieving expected benefits of cover crops.

The NT treatment significantly enhanced aggregate stability in our study by an additional 24%. Increases in aggregation have been previously linked to increases in soil biological activity and organic matter gains (i.e., Bottinelli et al., 2017; Kumar et al., 2012), but the NT treatment in our study was not significantly linked to increases in respiration, active carbon or organic matter gains. It has been strongly established that reductions in tillage, or any kind of disturbance, protects the structure of soil, the production of root exudates and the associated microbial activity that lead to aggregation, and these changes are easily detected *via* increased percentage of water stable aggregates (Wright et al., 1999; Kumar et al., 2012; Nouwakpo et al., 2018).

Despite the limited performance of the WCCC and NT treatments in this study, our analysis identifies the added benefits of combining cover crops with reduced tillage. A single year of no-till with cover cropping introduced at the end of our study significantly enhanced soil respiration by 0.16 CO_2 mg/g, aggregate stability by 24.8%, and organic matter by 0.26% in comparison to the continuous corn treatment, suggesting that combinations of conservation practices may have synergistic effects to enhance ecosystem service provisioning without compromising yields or crop quality, as has been identified by Kinoshita, et al. (2017) and Nunes et al. (2018). Specifically, the presence of plant roots, aboveground cover crop residues and no-till management have a synergistic effect on organic matter gains and aggregate stability through the production of glomalin by arbuscular mycorrhizal fungi associated with the roots of plants (Wright et al., 1999; Kumar et al., 2012). Tillage increases microbially mediated decomposition of organic matter and carbon losses by activating respiration with increased oxygen and release of CO_2. Soil aggregation also influences SOM decomposition. Aggregation physically protects SOM from microbial decomposition, and controls plant-derived SOM by occluding it into aggregates (Lagomarsino et al., 2012). In our study the measurable soil health benefits of cover cropping alone may have been negated by tillage. Conversely, the treatment with no-till alone lacked organic matter inputs or living roots and only influenced one soil health indicator.

Although reductions in tillage and disturbance can slow organic matter degradation and loss (Six and Paustian, 2014) the limited return of crop residues, and lack of manure or other organic matter inputs is likely key to explaining some of our findings across treatments. Corn crop residues and organic matter additions have been previously linked to the improvement of aggregate stability and organic matter (Nouwakpo et al., 2018). Return of crop residues is also linked to increases in soil organic matter content in no-till systems (Wang et al., 2020). Meta-analysis has linked crop residues to a 5% increase in yields (Lu, 2020). Due to the limited crop residue return in corn silage systems, the incorporation of cover crops or organic matter inputs to no-till systems is crucial to achieving the soil organic matter, carbon storage, and yield enhancements associated with long term no-till in other studies.

In our study a corn-hay rotation, with 2 years hay-6 years corn −2 years in hay (ROTC 2014), had significantly higher organic matter, and aggregate stability compared to CC in all years of the study. Enhanced aggregate stability and organic matter observed in perennial hay and corn rotation treatments align with established mechanistic understandings of soil qualities. Perennial crops have deeper, longer and stronger root systems than annual crops, which improves aggregate stability and can address compaction (Franzluebbers et al., 2000). The continuous supply of root exudates and root biomass in perennial systems that feeds biological activity in the soil, provides added organic matter and improves aeration and enhances nutrient cycling (Kumar et al., 2017).

The overall trend in organic matter in our study suggests that the reduction of organic matter decomposition through reduced tillage has a primary influence on organic matter gains in our study. Our study observed the WCCC treatment had a 10-year average of 0.0% additional organic matter, followed by the single year of NTCC with 0.26% more, and NT with 0.30% more. The treatment with perennial hay in rotation had the highest levels of organic matter. ROTC2020 had a 10-year average of 0.88% more, and ROTC2014 had 0.42% more. Organic carbon additions *via* roots and aboveground biomass are important to make greater gains, and align with aforementioned mechanisms of the synergistic influence between reduced disturbance and carbon additions to feed soil biology while also slowing losses (Six and Paustian, 2014; Kumar et al., 2017; Wang et al., 2020; Nunes et al., 2018).

Active carbon measures in the final year and across the 10-year average reflect the same pattern (Supplementary Material S2), with ROTC2020 having the highest level, then ROTC 2014, NT, NTCC, and WCCC with the lowest, although active carbon was only significantly influenced by the ROTC2014 treatment and the interaction of time with the ROTC2014 treatment. The model outputs, figure and mean detrended data over time indicate the effect of the treatment was variable over time, reflecting the rotation (Figure 3, Supplementary Material S2, Supplementary Material S3). Active carbon levels were 118 ppm greater in ROTC2014 than CC in 2013, and this difference was reduced over time when the rotation was planted with corn. In 2020, the ROTC2014 treatment had 5.36 ppm active carbon less than the CC treatment, and after it was rotated into perennial forage again the active carbon levels increased to 40 ppm greater than the CC treatment (Figure 3, Supplementary Material S2). Active carbon is a measure of biologically active soil carbon which is more sensitive to management effects than total organic carbon and is closely related to other measures of biological activity and organic carbon (Weil et al., 2003). Here, it illustrates that perennial hay has higher levels of biologically active carbon than continuous corn. When perennial grasses are rotated into corn there is legacy active carbon from the perennial grass plot which lasts approximately 2 years before reaching a similar level to continuous corn (Figure 3, Supplementary Material S2).

Our study found that available water capacity was only influenced by year. No-till, cover cropping, and even rotations with perennial grasses in corn silage forage production systems over a period of 10 years had no influence on the soil's capacity to infer drought resilience. This is likely due to the limited organic matter returns in these systems. Additions of manure, other organic matter sources, or higher biomass cover cropping could address this aspect of these annual forage productions systems and deserves more research.

4.2 Influence of treatments on yields and forage quality

The treatments NT, NTCC, WCCC, and ROTC2014 treatments evaluated in our study showed neither significant increase or decrease in overall dry matter yields. The long hay rotation, ROTC 2020, had significantly reduced yields compared to continuous corn. Perennial forages in rotation with corn may enhance ecosystem services and crop quality, but the length of time in rotation influences dry matter yields. Total dry matter yields were significantly reduced in the ROTC2020 treatment, with a 10-year average of 2.7 kg ha^{-1} less than continuous corn but were not significantly less over the 10-year time frame in the ROTC2014 treatment. Our evidence suggests that shorter rotations of perennial forages (4 years of hay, 6 years of corn) can sustain dry matter yields that are not significantly different from continuous corn over a 10-year time frame, but longer perennial forage rotations (8 years of hay, 2 years of corn) will significantly reduce overall dry matter yields over the 10-year time frame. Optimizing rotation durations for a balance of yields and ecosystem services is possible, and further research to optimize rotation length requires more inquiry and long-term research.

This ROTC2014 rotation did not significantly influence dry matter yields over the 10-year period when compared to CC treatments but had significantly higher CP concentrations. The ROTC2014 had a 10-year mean of 24.0% greater CP content than CC. At the annual level, significant differences were observed for both ROTC treatments in years which they were in hay (Table 6). In general, CP tends to be higher in cool-season grasses like meadow fescue than warm-season grasses like corn (Ball et al., 2001). The addition of legume in a perennial forage crop also increases CP and alfalfa is comparatively high in protein (Aponte et al., 2019). According to Capstaff and Miller (2018), "…alfalfa is the highest-yielding perennial forage legume and produces more protein per unit area than other forage legumes." This suggests that dairy farms in northern temperate climates could transition from continuous corn to corn-hay rotations without compromising overall yield and would improve forage quality, and at the same time enhance the soil's resilience to extreme precipitation events and storage of carbon. Species composition of hay plantings influences CP levels and should be researched in combination with hay-corn rotations to optimize forage system yields and quality. Rotations can help to diversify forage quality to meet the overall needs of livestock. Farmers seek to balance a feed ration that has significant energy and protein to maximize milk production and quality components. Protein and digestible fiber are produced by growing cool-season grass and legumes mixes (Ball et al., 2001; Aponte et al., 2019). Energy is produced by growing the starch found in corn silage. Additional grain is imported onto the farm to balance any nutritional shortfalls. As expected, rotations with perennial forage increased overall CP concentrations. Although perennial forage can be high in protein, an important component necessary for herd health, milk production, and quality milk, and has comparatively healthier soil and provisioning of associated ecosystem services, due to its lower yields and the need to grow energy, corn acres can take priority especially on prime agricultural land. This has implications for farm systems that move from continuous corn to perennial forage and expansion of land or conversion of land to agricultural production. Thus, optimizing rotations that sustain yields while increasing forage quality can reduce farm inputs and overall landscape footprint.

4.3 Future research needs

The results of our research provide rich fodder for future research on the sustainability of silage corn cropping management. Foremost, our study reflected typical management practice implementation for dairy farmers in the region of study, except that manure applications were not incorporated in the study. This allowed our research to focus on the impact of the practices of interest, but similar research that includes manure additions is needed, as manures are likely to influence soil health parameters though organic matter additions, as well as yields and crop quality through nutrient availability. Second, the limited impact of cover cropping identified in this study suggests that research on modifications to cover cropping implementation in these corn silage production systems is needed in order to establish practice standards among the farming community that will have both environmental and farm benefits. Alternative styles of cover cropping with greater species diversity, biomass, establishment dates or termination methods may enhance ecosystem services and yields in these systems, but carefully executed research is needed to identify which modifications provide the desired impacts. Third, our findings imply research on combinations of conservation practices (sometimes referred to as stacking) that quantify the benefits of management systems, rather than single practices, are needed to inform farmers, and conservation incentive program priorities.

Our research identified a corn-hay rotation that enhanced ecosystem services and sustained yields, but further research is needed to explore the optimization of rotation timings. This kind of research could explore optimization of rotations for yields while still enhancing ecosystem services, or optimization of rotations for ecosystem services that do not reduce yields. For example, there may be a "sweet spot" of a rotation with a longest possible interval of perennial forage yield which does not impact overall dry matter yields. Alternatively, there may be a low threshold for the interval of perennial forages in a rotation which prioritized yields but also sustains increases soil carbon storage over time.

Future research on corn cropping systems should also prioritize evaluation of how practices influence biological diversity, water quality, infiltration, and greenhouse gas emissions, preferably in long enough time frames to capture the temporal dynamics of rotations on outcomes of interest. As well, future research should replicate studies like ours to confirm these findings in different climates and soil types, as those factors often have a dominating influence on soil health characteristics and crop performance.

Our study identified a limited influence on yields from the cropping system adjustments in our study. If conservation practices do not result in increased yield or quality, farmers may have little incentive or financial capacity to adopt them. The costs incurred as labor, time, money, and stress to enhance ecosystem services provisioning are likely to limit adoption (White A. et al., 2021; White et al., 2022a). Incentivizing conservation practice implementation through market recognition, payment for ecosystem services program, land rental, or cost share programs is needed in light of our findings, and specific transdisciplinary research that identifies the economics costs of practices and the conservation inventive program preferences of farmers is needed to complement our findings.

5 Conclusion

Conservation practices and rotations can be implemented to sustain yields in corn silage production systems while also enhancing climate regulation, climate resilience, aspects of soil health, soil conservation and forage quality in temperate northern climates similar to Vermont, United States. However, in the absence of significant increases in yields over conventional management of continuous corn silage, conservation incentive programs are needed to enable farms to adopt these management changes that provide ecosystem services to society. Where farmers are limited in their land access and unable to accommodate perennial forage rotations on all fields, our research suggests that continuous corn silage production systems with low crop residue can be adjusted to enhance ecosystem services without compromising yields. Cover cropping with winter rye alone had no influence on ecosystem services, yields, or crop quality when compared to continuous corn. Despite the limited performance of the winter cover crop treatment in this study, our analysis identifies the added benefits of combining cover crops with reduced tillage. The inclusion of no-till management in corn production systems enhanced aggregate stability in our study, and therefore soil conservation and resilience to extreme precipitation, without compromising yields or crop quality. Thus, a combination of multiple conservation practices should be implemented together to achieve the greatest benefits, and more research that explores the long-term dynamics of practices in combination is needed. No-till in combination with cover cropping in corn silage fields, and a rotation of 4 years of hay to 6 years of corn are likely to achieve the greatest overall benefits in forage production systems. Dairy farms in northern temperate climates could transition from continuous corn to corn-hay rotations without compromising overall yield and would improve forage quality, and at the same time enhance the soil's resilience to extreme precipitation events and storage of carbon.

Our study identifies modifications to silage corn cropping agroecosystem management which can enhance ecological benefits, without sacrificing yields and forage quality, however careful consideration of rotation timings and practices in combination is necessary to achieve this potential. Significant time:treatment interactions indicate that the impact of corn cropping systems on soil health and yield are complex, dynamic, and can be variably affected by management practices. The quantification of these benefits as ecosystem services is valuable to informing the effectiveness and impact of conservation programs, and understanding trade-offs in dimensions of soil health. This highlights the importance of long-term datasets such as this in advancing our understanding of the environmental and economic implications of alternative cropping practices.

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

Conceptualization, AW and HD; Methodology, AW, HD, LR, and BS; Formal Analysis, AW, HD, LR, and BS; Investigation, AW, HD, LR and BS; Writing—Original Draft Preparation, AW, HD, and LR Writing—Review and Editing, AW, HD, LR, and BS; Visualization, AW; Project Administration, HD; Funding Acquisition, HD

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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/fenvs.2023.1061013/full#supplementary-material

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Evaluation of the policy options to adopt a water-energy-food nexus pattern by farmers: Application of optimization and agent-based models

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In recent years, water-scarce regions (WSRs) have faced many challenges in order to achieve sustainable economic development. Sustainable economic development in the agricultural sector of WSRs is possible by paying attention to the water-energy-food nexus (WEFN) concept. WEFN determined using consumption, physical productivity, and economic productivity criteria of water and energy resources. According to the goals of physical and economic productivity of water and energy resources, it will be very difficult to implement WEF nexus patterns in WSRs with severe water resource crisis. The present study is aimed in WSRs to extract the resource allocation pattern based on the goals of the WEFN system using multi-criteria decision making (MCDM) tools and evaluate the cooperative behavior of farmers with this pattern under government's policy options using an agent-based model (ABM). The results for Doroodzan dam irrigation network as a WSR revealed that the pattern based on WEFN will lead to a 200 and 18 percent increase in physical and economic water productivity and a 156 and 67 percent increase in physical and economic energy productivity compared to the base pattern, but the implementation of this pattern requires 33% more water consumption. Therefore, it is very necessary to water resource management policies such as using modern irrigation technologies under government policy options in order to implement the pattern based on WEFN in WSRs. In this regard, the inflexibility of the government's policies will prevent the widespread implementation of the pattern based on WEFN and sustainable economic development at the regional level. Also, it can be concluded that the expansion of sustainable patterns in the agricultural sector will not be possible without considering the situation of the region from the point of view of water resources and also the cooperative behavior of the farmers. Finally, the framework of the present study is recommended to achieve the goals of sustainable economic development of the agricultural sector in WSRs.

KEYWORDS

water-energy-food nexus (WEFN), water-scarce regions (WSRs), multi-criteria decision making (MCDM), agent-based model (ABM), water-scarce regions

1 Introduction

In recent years, the increase in demand for agricultural products arising from population growth, economic development and urbanization has resulted into an increase in water and energy use for food production (Karabulut et al., 2016; Radmehr et al., 2021). A global shortage of food caused by increasing competition for the consumption of limited water and energy resources in the agricultural sector along with climate change is a predictable event (Steffen et al., 2015; Pastor et al., 2019; Abdelkader and Elshorbagy, 2021). Agriculture accounts for about 90% of fresh water consumption and about 30% of energy use around the world (FAO, 2011). On the other hand, agricultural irrigation provides about 40% of the world's food (Li et al., 2022). Thus, water, energy and food, as the basic needs of human life, are regarded as important components for sustainable economic development studies of human communities (Wen et al., 2022).

The analysis of the water-energy-food nexus (WEFN) is necessary for sustainable management of water and energy resources in the agricultural sector and ensures food security, namely in water-scarce regions (WSRs) around the world (Stephan et al., 2018; Mirzaei et al., 2022a). The WEFN term was proposed in early 2010 for the integrated management of the three critical resources of water, energy and food (Hoff, 2011; Scott et al., 2015; Vanham et al., 2019; Guan et al., 2020). Several conceptual frameworks have been designed to analyze the WEFN (Gain et al., 2015; Mayor et al., 2015; Guan et al., 2020). In various studies, WEFN has been analyzed through life cycle (Albrecht et al., 2018), water footprint theory (Hung, 2002; Ramaswami et al., 2017; Zhang et al., 2019; Lee et al., 2020), optimization models (Jalilov et al., 2016; González-Bravo et al., 2018; Li et al., 2019a; Li et al., 2019b; Wicaksono and Kang, 2019; Sun et al., 2020; Yu et al., 2020; Radmehr et al., 2021; Mirzaei et al., 2022a; Li et al., 2022), input-output data (Xiao et al., 2019), social analysis (White et al., 2017) composite sustainability indices (Dizdaroglu, 2017; El-Gafy et al., 2017; Farinha et al., 2019; Nhamo et al., 2020; Sadeghi et al., 2020; Saray et al., 2022) and system dynamics models (Wa'el et al., 2018; Hu et al., 2019; Tan and Yap, 2019; Wen et al., 2022).

Considering the relationship between water, energy and agriculture sectors and the different goals of these sectors (Chen et al., 2017; Yu et al., 2020), it is necessary to use multi-objective and multi-criteria decision-making models, because considering only the goal of one sector of the three sectors of water, energy and food, may result into misleading results (Bizikova et al., 2013). Therefore, providing a composite index by including all criteria related to water, energy and food can be used as a comprehensive tool to examine the aspects and concerns related to all three sectors (El-Gafy et al., 2017; Nhamo et al., 2020; Sadeghi et al., 2020). For example, Nhamo et al. (2020) estimated the WEFN index using Analytical hierarchy process (AHP) method as a multi-criteria decision-making method. In this study, the WEFN index was calculated as a sustainable development index for South Africa in the two time periods of 2015 and 2018 and the sustainability condition was also evaluated. Radmehr et al. (2021) used the multi-objective optimization model with the goal of maximizing the benefits of the agricultural, urban and industrial sectors and minimizing the destruction of groundwater resources with the restrictions of water and energy resources, and extracted a set of optimal Pareto solutions. Also, by using multi-criteria decision-making methods, and the criteria related to WEFN, they selected the best solution and proposed the appropriate cropping pattern. Sadeghi et al. (2020), Mirzaei et al. (2022a) and Saray et al. (2022) combined the criteria related to the linkage between the water, energy and food sectors, and calculated the WEFN index for different crops in a studied area and then maximized the WEFN index along with other economic and environmental goals using the optimization models.

On the other hand, the optimal agricultural management with the WEFN approach will not be efficient without considering the cooperative behavior of farmers (Radmehr et al., 2021). Hoolohan et al. (2018) argued that stakeholders play a very important role in the development of WEFN tools. Thus, the main focus of this study is the analysis of farmers' cooperation with the extracted patterns obtained from the goals of the WEFN system. By determining an optimal pattern without the adequate cooperation of farmers to implement this model, we observe failure at the operating level definitely. In other words, it is necessary to examine the operational and applicability of the optimal patterns at the regional level, as agent-based models (ABM) are used to simulate these behavioral and social complexities on a wide scale, namely in the water resources management (Bandini et al., 2009; Akhbari and Grigg, 2013; Farhadi et al., 2016; Mirzaei and Zibaei, 2021; Mirzaei and Azarm, 2022). For example, Akhbari and Grigg (2013) investigated consumer conflict resolution in the San Joaquin watershed in California using the ABM. In this study, the three objectives of maximizing water withdrawal for agricultural purposes, maximizing the water output to the wetland and minimizing the salt loaded by the water used in agriculture were considered as the purposes of the study and an optimal and applicable solution at the basin level was presented. Farhadi et al. (2016) used an ABM framework for the sustainable management of groundwater in Darayan, Maharlo, Tashk and Bakhtegan lakes in Fars province in Iran. For this purpose, a multi-objective optimization model was used with the purpose of reducing irrigation water, increasing equality in water allocation and reducing groundwater extraction in order to achieve Pareto optimal solution and Nash bargaining model to achieve a consensus among the stakeholders. Then, an ABM model was implemented to examine social factors and policy mechanism to encourage stakeholders to participate in management decisions. Using the ABM, Mirzaei and Zibaei (2021) evaluated the participatory behavior of farmers with optimal patterns under the effect of adaptive strategies to climate change in the Halil River basin with the aim of reviving the Jazmourian wetland in this basin.

According to the literature review, multi-objective mathematical programming methods have been applied in order to achieve the goals of the WEFN and to determine an appropriate pattern for these goals. However, the present study attempts to determine the pattern of resources optimal allocation in a WSR by using multi-criteria decision-making methods and considering the goals of the WEFN. Despite multi-objective mathematical programming

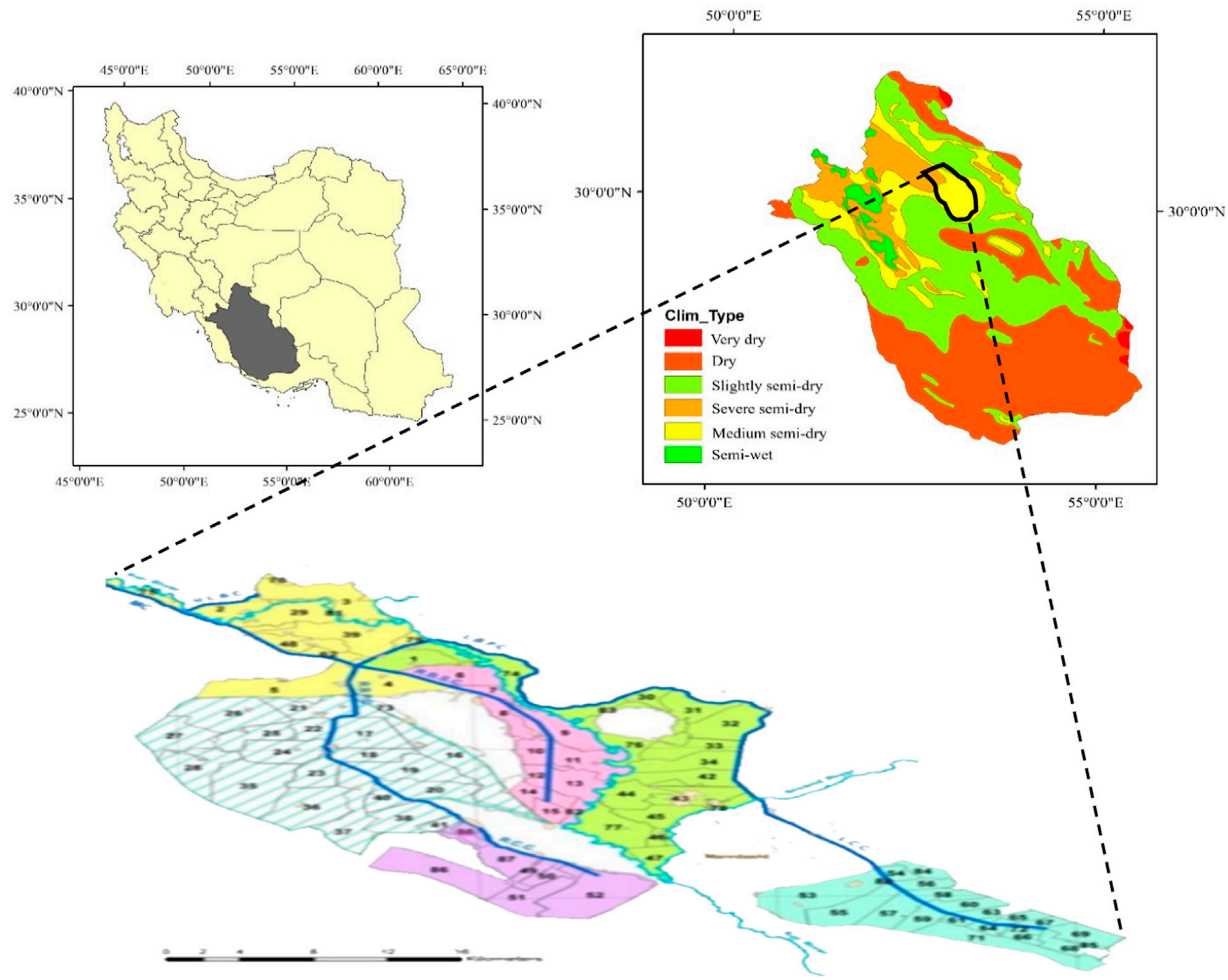

FIGURE 1
Location of irrigation network of doroodzan dam in fars province, Iran.

methods, this evaluation method formulates complex issues, criteria and goals simply, and extracts suitable solutions by considering the opinion of experts and decision makers (Nhamo et al., 2020). On the other hand, no study has been conducted in the world to examine the participatory behavior of farmers with patterns extracted from the WEFN system, and this study is considered the first one in this field. Thus, the present study is aimed to extract the cropping pattern and resources allocation based on the goals and criteria of the WEFN system in an arid and semi-arid region with serious water resource scarcity (WSR) through multi-criteria decision-making methods and then analyzing the cooperative behavior of farmers and the government's policy options to encourage farmers with an extracting model. For this purpose, the irrigation network of Doroodzan dam in Fars province, Iran is considered as a WSR.

2 The study area

Fars province in Iran is one of the most important agricultural regions, and it is considered one of the WSRs of the world. The average rainfall in this province was about 322 mm during the years 1992–2013, and this province encountered severe droughts between 2003 and 2011 (Mirzaei et al., 2022b). Also, predictions indicate that in the future, the temperature will increase and soil moisture will decrease in Fars province (Gandomkar and Dehghani, 2012). Doroodzan Dam basin in Fars province is one of the most important regions in Iran, and Bakhtegan Lake is located at the end of this region. This lake is the second largest lake in Iran in terms of size and is classified as a national park (Tarazkar, 2016). This lake is fed by Kor River, which originates from the heights of the Zagros mountains. Doroodzan dam's irrigation network (Ramjerd plain irrigation network) is one of the important agricultural areas in this basin, which is considered as the study area. This irrigation network is located in the northwest of Fars province and is fed from the outlet of Doroodzan Dam (Figure 1). The water released from the Doroodzan Dam enters the main channel of the irrigation network of the Doroodzan and before reaching the water distribution structure, a part of water is allocated for

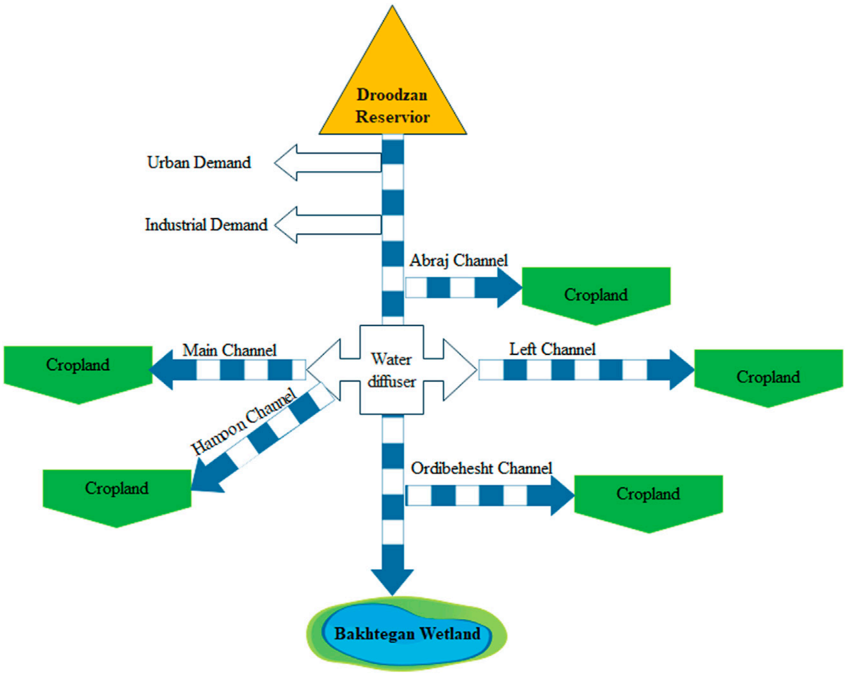

FIGURE 2
Schematic of the irrigation network channels of doroodzan dam.

drinking and industrial purposes. Also, the Abraj canal is located before the distribution water structure. In the distribution water structure, the water branches into 4, main, left, Hamon and Ordibehesht canals. Abaraj canal, which is located before the water distribution structure, has a length of about 5 km and this canal covers 1934 ha of agricultural land. The canals branched from the distribution water structure include the main, left, Hamoon and Ordibehesht canals, which have a length of 22, 67, 34 and 22 km, respectively, and each of these canals cover about 6,108, 22,096, 15,946 and 5,430 ha of agricultural fields (Figure 2).

3 Materials and methods

3.1 Data

In the present study, the data required to extract the resources allocation pattern based on the WEFN, including the information related to the technical coefficients of the production inputs and the crops production cost, were extracted from the farmers of the study area *via* the design of questionnaires and interviews. For this purpose, a sample of farmers supported by the irrigation network of Doroodzan Dam was chosen using multi-stage random sampling method. In this way, at first, the villages covered by this irrigation network were divided into three categories, low, medium and high by the clustering method, based on the amount of water withdrawal. Then, some villages were selected using simple random sampling from each category according to the total number of villages in that category. Finally, 100 sample farmers were determined based on the population of farmers in the villages using the simple random sampling method. Also, the data related to the cultivation area, the amount of water resource consumption, crop yield and the amount of consumption of other production inputs per unit area, are based on agricultural service centers, agricultural jihad and Fars regional water Company. Then, a pair-wise comparison questionnaire of the WEFN criteria was completed *via* 10 economic and environmental experts and, the weight of the WEFN criteria was calculated in accordance with this information. Ultimately, in order to analyze the ABM, interviews were conducted with the sample farmers in the study area and the given policy options were shared with them.

3.2 Conceptual framework

The conceptual framework of the study is depicted in Figure 3. The criteria related to the WEFN were determined according to the review of the literature in this field (El-Gafy et al., 2017; González-Bravo et al., 2018; Nhamo et al., 2020; Sadeghi et al., 2020; Radmehr et al., 2021; Mirzaei et al., 2022a; Saray et al., 2022). The energy consumption data in the production of different crops can be calculated *via* the energy equivalent of the consumption production inputs (El-Gafy et al., 2017; Sadeghi et al., 2020). The water and energy physical productivity criteria (Wp and Ep) for different crops (c) are

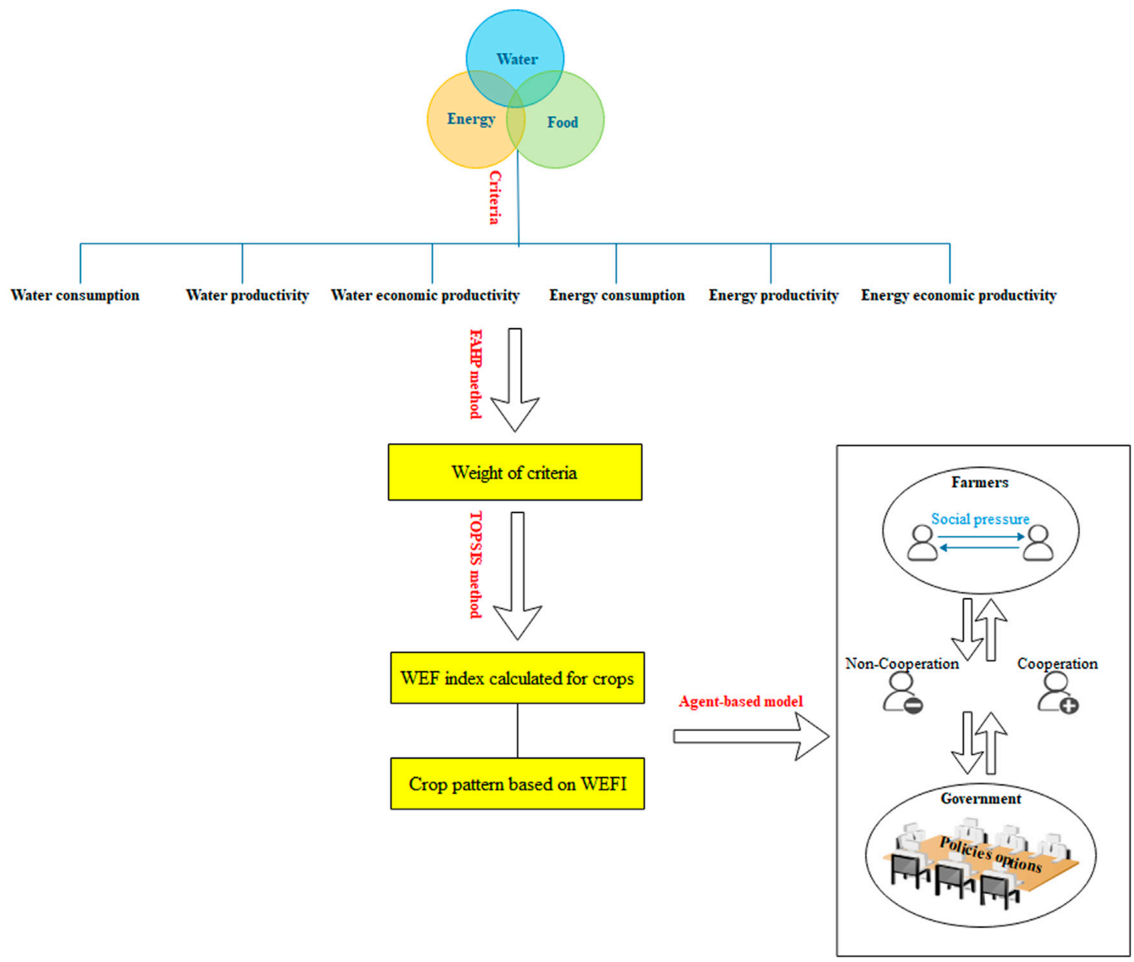

FIGURE 3
Conceptual framework of the present study.

obtained from the ratio of crop yield (Y) to the amount of water and energy consumption (W and E) of that crop per unit area.

$$Wp_c = \frac{Y_c}{W_c} \tag{1}$$

$$Ep_c = \frac{Y_c}{E_c} \tag{2}$$

The water and energy economic productivity measures (Wep and Eep) were also obtained from the ratio of the gross margin (GM) of the crop to water and energy consumption of that product per area unit.

$$Wep_c = \frac{GM_c}{W_c} \tag{3}$$

$$Eep_c = \frac{GM_c}{E_c} \tag{4}$$

In the second stage, the weight of the importance of these criteria was obtained from the experts' opinion (Nhamo et al., 2020). For this purpose, the WEFN index was calculated by separating the crops in the cropping pattern using the fuzzy analytic hierarchy process (FAHP) method and then the TOPSIS method. In the third step, based on the existing cultivation area, the cropping pattern was determined according to the WEFN index. In the final stage, the resources allocation pattern based on the WEFN along with the policy options was shared with the given sample farmers and the cooperation or non-cooperation of farmers with the proposed model with and without the government's policy options was evaluated by the ABM. (Akhbari and Grigg, 2013; Akhbari and Grigg, 2015; Guo et al., 2022; Mirzaei and Azarm, 2022).

TABLE 1 The performance matrix of TOPSIS method.

Crops	Criteria 1	Criteria 2	...	Criteria m
Crop 1	a_{11}	a_{12}	...	a_{1m}
Crop 2	a_{21}	a_{22}	...	a_{2m}
...	...	...	...	...
Crop n	a_{n1}	a_{n2}	...	a_{nm}
Weight of criteria	W_1	W_2	...	W_m

3.3 Research methods

3.3.1 FAHP and TOPSIS

In the present study, the Fuzzy Analytic Hierarchy Process (FAHP) is used which was presented by Chang in 1996 as a quantitative analysis method (Chang, 1996). All the calculations related to the FAHP process are based on the decision maker's initial judgment in the form of pairwise comparison matrices. The compatibility indices were used in order to evaluate the compatibility of decision makers' responses. After calculating the value and weight of the relative importance of WEFN criteria for different crops, the performance matrix was formed and, it was prioritized and determined the share of crop cultivation using the TOPSIS method (Table 1).

According to Table 1, W denotes the importance weight of criteria calculated *via* FAHP method and elements a_{nm} are the calculated values of each crop for different criteria. The TOPSIS method, which selects the shortest distance from the ideal solution as the best option, is part of the category of compromise or agreement methods with the following steps:

1) At first, the maximum value is the best for some criteria, and the minimum is the best for other criteria. Therefore, the ideal alternative is as follow:

$$A^{+} = \left\{A_1^{+}, A_2^{+}, ..., A_j^{+}\right\} \tag{5}$$

2) In the second stage, for the best maximum criteria, the lowest value and for the minimum best criteria, the highest value was identified and the anti-ideal alternative was formed.

$$A^{-} = \left\{A_1^{-}, A_2^{-}, ..., A_j^{-}\right\} \tag{6}$$

3) In the last step, the proximity index related to each option (product) was calculated through the following formula:

$$CI = \frac{(R)^{-}}{(R)^{+} + (R)^{-}} \tag{7}$$

Where R^- is the distance of each alternative from the worst option and R^+ is the distance of each alternative from the ideal option. Next, to evaluate the share of each crop in the cropping pattern, the closeness index was normalized. Thus, the closeness index of each crop was divided by the sum closeness index of the crops and the share of each crop in the cropping pattern based on WEFN was calculated.

3.3.2 Agent based model (ABM)

The ABM was used to investigate the cooperative behavior of farmers with the resources allocation pattern based on WEFN system. Since the proposed pattern based on the WEFN is obtained through multi-criteria methods, it does not consider the limitation of water resources like mathematic programming models. Thus, in a region with water scarcity crisis, there are many challenges to implement the proposed resources allocation pattern. Therefore, in order to implement the resources allocation pattern based on WEFN in a WSR, it is necessary to evaluate the strategies to increase water efficiency along by incentive policies.

The key factors in the implementing of ABM model are (Makall and North, 2006): 1) definition of agents, 2) precise determination of agents behaviors, 3) definition of the environment in which agents are located, 4) determination of the relationship between agents, and the development of a theory about the interaction of agents with each other and with the environment, 5) the development of data related to agents, 6) the appropriate presentation of the interaction of agents with each other and agents with the environment, 7) evaluation of the accuracy of the behavioral model agents.

The ABM proposed in the present study is planned to provide a tool that helps to find effective policies options to encourage farmers to cooperate with a cultivation pattern based on WEF nexus. In this ABM model, agents include farmers and government or policy-making organizations in the agricultural sector. Farmers seek to maximize their utility from crop cultivation, and policy-making organizations seek to encourage farmers to follow the proposed cultivation pattern. The environment in the present study determines the proposed cultivation pattern, which is an optimal and sustainable pattern based on WEF nexus objectives. The interaction of farmers with each other are defined based on social pressures and the relationship between farmers and the government/policy-making organizations are designed based on incentive policy options. Data related to agents are obtained based on existing policy conditions and questions from farmers. In the end, a triangular utility function is used to validate the model, based on which it is possible to understand whether the policy options can increase the utility of farmers compared to the existing conditions and encourage them to follow the proposed cultivation pattern more.

Figure 4 shows the structure of the proposed ABM to formulate this model. At first, farmers' decisions are based on profit of proposed pattern compared to current profit. Therefore, if the profit of the proposed model is more than the current model, they participate with the proposed pattern and *vice versa*. Then, the effects of the social pressures of farmers on each other and the changes in farmers' decisions are evaluated. In the third stage, the government's incentive policies options are investigated in order to encourage the cooperative farmers to continue their decision and incite no-cooperative farmers to change their decision.

Farmers' utility to continue or change their behavior was measured based on the social pressures and government policy options (Edwards et al., 2005; Farhadi et al., 2016; Mirzaei and Zibaei, 2021; Mirzaei and Azarm, 2022).

$$U_i = max\left\{\begin{array}{l} U_i(C \to C) = a \times S_i(C) + P_m \\ U_i(C \to NC) = b \times S_i(NC) \end{array}\right\} \tag{8}$$

$$U_i = max\left\{\begin{array}{l} U_i(NC \to C) = c \times S_i(C) + P_m \\ U_i(NC \to NC) = d \times S_i(NC) \end{array}\right\} \tag{9}$$

As shown in the equations, the cooperative farmer decides to continue his behavior or change his cooperative behavior according to the utility obtained. For a cooperative farmer, $U_i(C \to C)$ and $U_i(C \to NC)$ indicate the desirability of this farmer, respectively by continuing cooperative behavior and changing behavior from

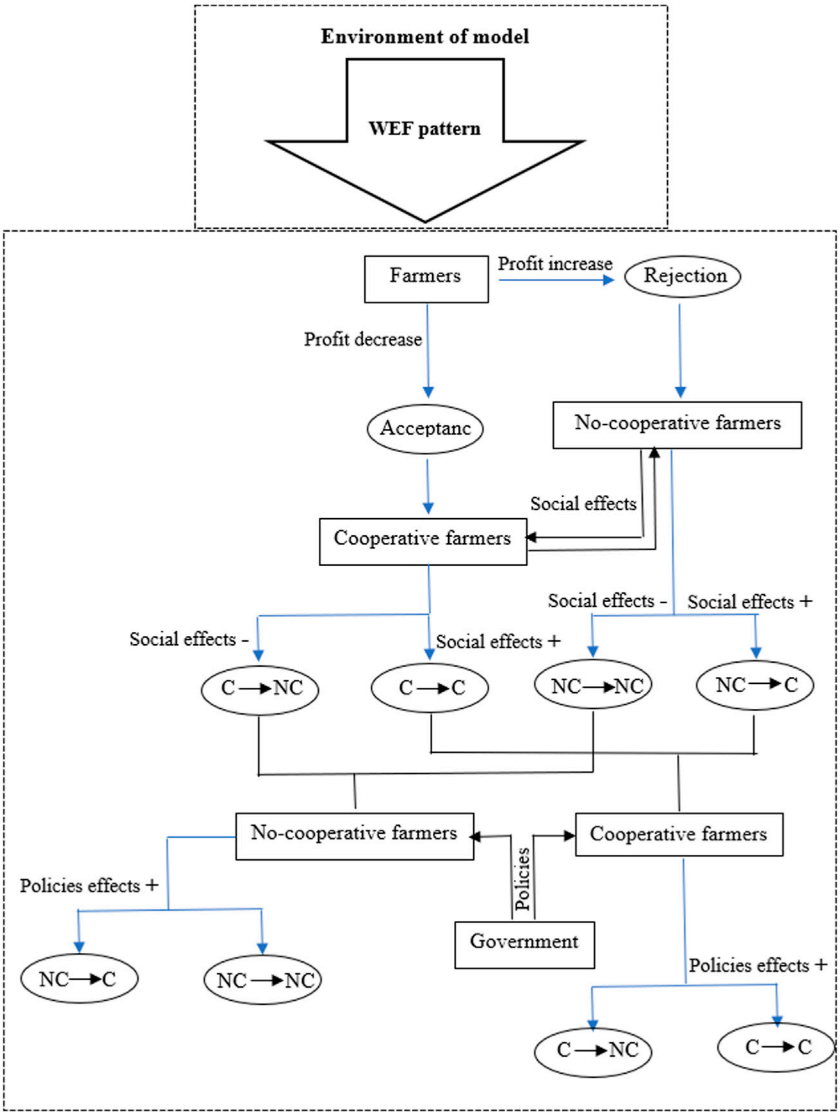

FIGURE 4
ABM formulation structure.

cooperation to non-cooperative with the proposed pattern (Eq. 4). Also, for a non-cooperative farmer, $U_i(NC \rightarrow C)$ and $U_i(NC \rightarrow NC)$ indicate the utility of this farmer by changing his behavior towards cooperation and continuing non-cooperative behavior, respectively (Eq. 5). In these Equations, utility is a function of social pressures and incentive policies of the government. To calculate social pressures, $S_i(C)$ and S_i (NC) are the ratio of cooperative and non-cooperative farmers to the total farmers in the present sample, respectively. Parameters a and b are equal to 0.7 and parameters c and d are equal to 0.3 (Edwards et al., 2005; Akhbari and Grigg, 2013; Farhadi et al., 2016; Mirzaei and Zibaei, 2021). P_m also indicates the incentive policy options of the government. The lack of P_m in the utility function indicates the absence of policy options to persuade farmers to participate in the proposed pattern. For quantification of the government's incentive policy options, it is necessary to calculate the level of farmers' utility with each of the policy options. It is worth to mention that there are

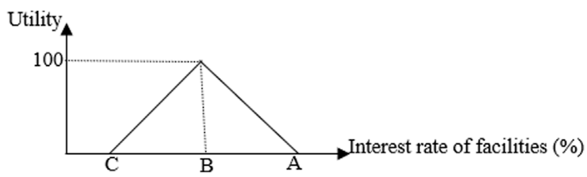

FIGURE 5
- Farmers' utility function.

many different incentive strategies; however, incentive solutions should be acceptable by the government and government institutions. Thus, in the present study, the motivational solution of granting facilities to develop the use of new irrigation technologies is taken into consideration. Then, the farmers were asked three basic

TABLE 2 The current cultivation area and calculated criteria of WEFN.

Crops	Area (ha)	WC (M3/ha)	EC (Mj/ha)	WP (kg/m3)	EP (kg/Mj)	WEP ($/M3)	EEP ($/Mj)
Wheat	36,060	11,562	46,260	0.429	0.107	0.0311	0.0078
Barley	5,151	9,445	37,524	0.333	0.084	0.0240	0.0060
Rapeseed	515	10,450	39,321	0.308	0.082	0.0226	0.0060
Rice	2061	28,000	46,776	0.154	0.092	0.0472	0.0283
Tomato	2060	20,728	47,556	3.582	1.561	0.0467	0.0204
Green-maize	5,150	14,017	38,985	4.467	1.606	0.0315	0.0113

WC, water consumption; EC, energy consumption; WP, water physical productivity; EP, energy physical productivity; WEP, water economic productivity; and EEP, energy economic productivity.

questions to extract the utility function with and without this motivational solution as:

A) The interest rate of the facility, on that value or above it, no utility is obtained.
B) The interest rate of the facility in which the maximum utility is achieved.
C) The interest rate of the facility, as on that amount and lower than that, no utility is obtained (Based on this value, you feel that the banks and the government will be at loss, and you do not consider this value to be reasonable for the progress of the project in the long term). Therefore, the given utility function is a triangular function (Figure 5).

4 Results and discussion

According to the concept of WEFN, water and energy consumption criteria, water and energy physical productivity, and water and energy economic productivity were calculated in the Doroodzan Dam irrigation network (Table 2). It is worth noting that the amount of energy consumption of different crops is calculated by the equivalent energy consumption and the consumption of production inputs of machinery, labor, fertilizers and pesticides, electricity, fuel, irrigation water and seed. The energy consumption of different inputs in the manufacturing of products is also based on the study done by Sadeghi et al. (2020).

The total cropping area covered by the irrigation network of Doroodzan Dam is about 51,514 ha, and the major crops in Table 2 cover 50,997 ha of these fields (about 99%). According to the results of Table 2, the largest amount of cropping area is dedicated to wheat with about 71% share of the cropping pattern. Rice and barley have the highest and lowest water consumption with 28,000 and 9,445 cubic meters per hectare, respectively. The highest and lowest amount of energy consumption is related to the two crops of tomato and barley with 47,556 and 37,524 MJ per hectare. The highest amount of water physical productivity is dedicated to the two crops of green-maize and tomato with 4.467 and 3.582 Kg/M^3 respectively, and the rice crop has the lowest amount of water physical productivity with 0.154 Kg/M^3. In the studies of El-Gafy et al. (2017), El-Gafy (2017) and Radmehr et al. (2021), water physical productivity for tomato crop was evaluated more than other crops, and the high level of physical productivity of water for green-maize in the studies of Mirzaei et al. (2022a) and Saray et al. (2022) has been indicated. In addition, green-maize and rapeseed crops have the highest and lowest energy physical productivity with 1.606 and 0.082 kg/MJ, respectively. Energy physical productivity for green-maize in the studies of Mirzaei et al. (2022b) and Saray et al. (2022) is also examined more than other crops. Finally, based on both criteria of water and energy economic productivity, tomato has the highest value among the studied crops with 0.0472 dollars per M^3 of water economic productivity and 0.0283 dollars per Mj of energy economic productivity. Despite tomato, rapeseed has the

TABLE 3 The normalized performance matrix of TOPSIS method.

Crops	WC	EC	WP	EP	WEP	EEP
weight	0.17	0.07	0.24	0.12	0.26	0.14
Wheat	0.277	0.440	0.074	0.048	0.360	0.203
Barley	0.226	0.357	0.058	0.037	0.278	0.156
Rapeseed	0.250	0.374	0.053	0.036	0.262	0.156
Rice	0.671	0.445	0.027	0.041	0.547	0.736
Tomato	0.497	0.452	0.622	0.695	0.541	0.531
Green-maize	0.336	0.371	0.775	0.715	0.365	0.294

TABLE 4 The weighted normalized performance matrix and ideal and anti-ideal alternatives.

Crops	WC	EC	WP	EP	WEP	EEP
Wheat	0.047	0.031	0.018	0.006	0.094	0.028
Barley	0.038	0.025	0.014	0.004	0.072	0.022
Rapeseed	0.043	0.026	0.013	0.004	0.068	0.022
Rice	0.114	0.031	0.006	0.005	0.142	0.103
Tomato	0.084	0.032	0.149	0.083	0.141	0.074
Green-maize	0.057	0.026	0.186	0.086	0.095	0.041
Action	min	min	max	max	max	max
Ideal	0.038	0.025	0.186	0.086	0.142	0.103
Anti-Ideal	0.114	0.032	0.006	0.004	0.068	0.022

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TABLE 5 The closeness index of crops, share and amount of cultivated area of crops based on WEFN.

Crops	$(R)^+$	$(R)^-$	CI	S	Area
Wheat	0.207	0.073	0.261	0.101	5,151
Barley	0.218	0.076	0.259	0.101	5,151
Rapeseed	0.221	0.072	0.246	0.096	4,896
Rice	0.211	0.110	0.342	0.133	6,782
Tomato	0.066	0.188	0.741	0.288	14,687
Green-maize	0.080	0.208	0.722	0.281	14,330

lowest economic productivity of water and energy with 0.0226 and 0.0060, respectively. In the studies conducted by El-Gafy et al. (2017) and El-Gafy (2017), two crops of onion and tomato have the highest economic productivity of water and energy. However, in the study of Sadeghi et al. (2020), onion has the highest economic productivity of water and energy among crops.

According to the information in Table 2 and also the weight of the importance of WEFN index criteria, the value of the index was calculated separately for different crops. For this purpose, at first, the weights of the WEFN criteria were calculated *via* the FAHP method, and then the closeness index of the crops was calculated using the TOPSIS method based on the examined criteria, which indicates the WEFN index for different crops. Thus, first the normalized performance matrix was calculated (Table 3). Then, the weighted normalized performance matrix was extracted from the product of the weights of the criteria in the resulting normalized values and ideal and anti-ideal alternatives were extracted based on the action of each criterion (Table 4). Finally, the closeness index of crops, and the share and amount of crops in the proposed cropping pattern were determined (Table 5).

The results of Table 5 showed that the share of tomato, green-maize and rice in the cropping pattern is higher than other crops. Based on this finding, the proposed pattern based on WEFN does not necessarily recommend reducing the share of water-intensive crops in the cropping pattern. In the studies done by El-Gafy et al. (2017), Nahidul Karim and Daher (2021), Saray et al. (2022), and Li et al. (2022), the high share of the cropping area of water-intensive crops in the proposed pattern based on WEFN is confirmed. For example, Li et al. (2022) argued that if there are adequate water resources in a region, the share of rice crop in the WEFN is increased. In the study of Saray et al. (2022), the high share of the cultivated area of green-maize in the WEFN-based cropping pattern has also proved. However, in the studies of Yu et al. (2020), Sadeghi et al. (2020), Radmehr et al. (2021) and, Mirzaei et al. (2022a) due to the limitation of water resources in the mathematical programming model, the WEFN-based cropping pattern suggested reducing the share of the cultivated area of water-intensive crops. Therefore, it is concluded that the implementation of the pattern based on WEFN at the level of the irrigation network of Doroodzan Dam, which is encountering a water resource crisis, may not be possible. For a better understand of the conditions of resources allocation, the WEFN criteria in this pattern was compared with the current cultivation pattern (Figure 6).

Figure 6. Showed that in the proposed pattern based on WEFN, all the criteria except the water consumption criterion will be improved compared to the current pattern. Water consumption is such that in the pattern based on WEFN, it will increase by 33% compared to the current conditions. Also, among the criteria, the physical productivity of water and energy experiences the highest improvement with 200% and 156%, respectively. The WEFN pattern is an optimal pattern from the perspective of sustainability due to the improvement of the physical and economic productivity criteria of water and energy, but the water consumption in this pattern is increased compared to the current conditions. Hence, the operationalization of this pattern will not be possible due to

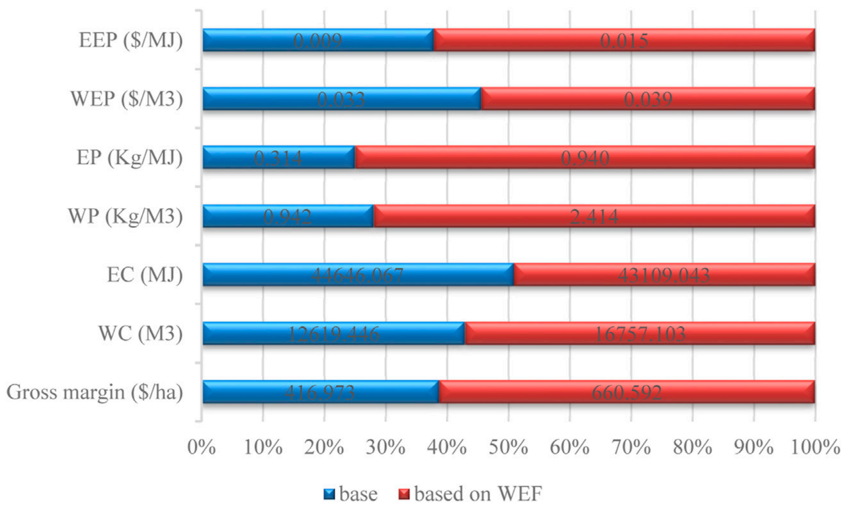

FIGURE 6
Comparison of current and proposed WEFN-based patterns.

TABLE 6 The level of cooperation and non-cooperation of farmers with policy options.

Title	S_1[a]	S_2[b]	S_1 and S_2
Number of Cooperatives	37	81	24
Number of Non-Cooperatives	63	19	76
Total	100	100	100

[a]: S_1 is Irrigation modern technologies.
[b]: S_2 is pattern based on WEFN.

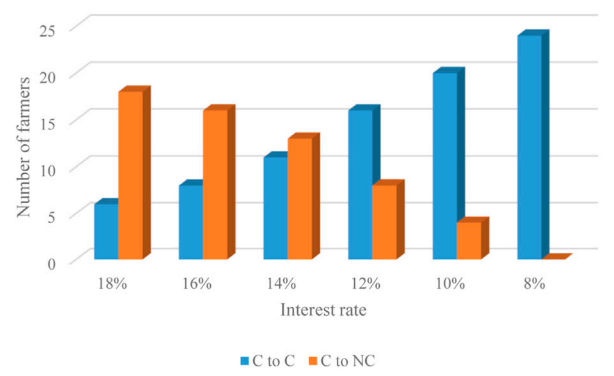

FIGURE 7
Analysis of the behavior of cooperative farmers with S1 and S2 policies. (C to C: Continue cooperative behavior and C to NC: Changing from cooperative to non-cooperative behavior).

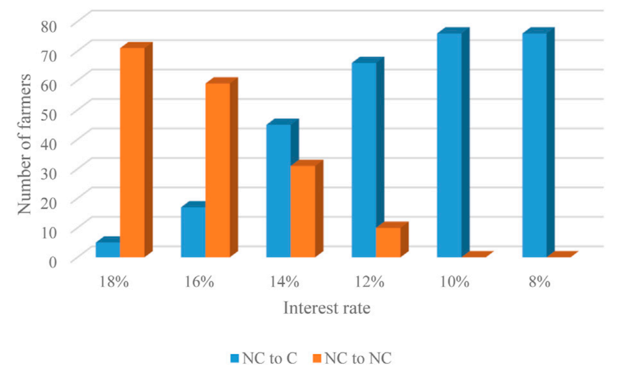

FIGURE 8
Analysis of the behavior of non-cooperative farmers with S1 and S2 policies. (NC to C: Changing from non-cooperative to cooperative behavior and NC to NC: Continue non-cooperative behavior).

the conditions of water resources in arid and semi-arid regions. In this study, we should implement policies to reduce water consumption to achieve the WEFN-based pattern. For this purpose, the policies of adopting new irrigation technologies, improving water transfer channels to farms, plastic covering of crops on the farm, etc. Can reduce water consumption in order to achieve the WEFN-based model (Mirzaei and Zibaei, 2021). For example, the policy of developing the use of new irrigation technologies at the farm level was evaluated considering the farmers' behavior in order to analyze the implementation of the WEFN-based pattern. To do this, the sample farmers of the study area were asked about their cooperation and non-cooperation in using new irrigation technologies and implementing the pattern based on the WEFN in order to reduce water consumption and achieve the goals of the WEFN (Table 6).

Table 6 indicated that 37 individuals (percent) of the farmers in the present sample adopt new irrigation technologies as an approach to reduce water consumption, and 63 individuals (percent) of them do not use this strategy. In other words, the strategy of developing the use of new irrigation technologies is encountered with the resistance of most farmers in this region. Also, the implementation of the proposed pattern based on the WEFN was shared with the farmers in the present sample and it was found that 81 individuals (percent) of the farmers considered the water scarcity as the main problem for the implementation of such a pattern and stated that by increasing the water allocation, this pattern is implemented. The reason for the high adoption of the proposed pattern is that this pattern provides good economic returns to farmers (the results of Figure 6 indicated that the economic return in the proposed pattern based on the WEFN has increased by about 53% compared to the current pattern). Also, 19 farmers in the present sample are not willing to participate despite the high productivity of the proposed pattern based on WEFN, which is due to the resistance and inflexibility of these farmers to change cropping from a crop such as wheat to some crops such as tomatoes and green-maize. Finally, the simultaneous adoption of expansion of the use of new irrigation technologies and the implementation of the proposed pattern based on the WEFN to achieve the goals of reducing water consumption and sustainable development were asked and it was found that only 24 individuals (percent) of the sample participated in this project. Therefore, it can be found that the implementation of new irrigation technologies combined with the WEFN pattern will not be applicable due to the mental resistance of farmers to changing the irrigation technology and cropping pattern. Thus, it is required to evaluate the social pressures of farmers on each other as well as the incentive policies of the government in order to change the attitude of farmers towards participation with the plan. Granting facilities to farmers to develop new irrigation technologies is one of the most prevalent incentive policies in Iran. Therefore, the behavior of 24 cooperative farmers and 76 non-cooperative farmers was analyzed based on the effects of farmers' social pressures on each other and the policy of granting facilities with different interest rates (Figures 7, 8).

The results demonstrated that the granting of facilities in an interest rate of 18% (the rate of the majority of facilities given in Iran) causes that only six cooperative farmers remain in a cooperative state and 18 of them have changed their behavior and they are not willing to accept the proposed plan. Despite the encouraging scenario of granting facilities for the development of new irrigation technologies, this behavior change is caused by the social pressures of farmers, because the attitude of the majority of the present sample is not cooperative (76 people out of 100) and this will lead to a change in the behavior of cooperative farmers. As shown in Figure 7, the reduction of the interest rate of facility makes more

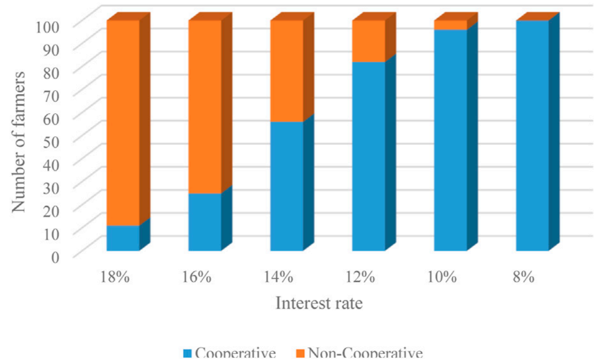

FIGURE 9
The level of cooperative and non-cooperative of farmers under social pressure and incentive policy options.

cooperating farmers continue their cooperative behavior with the proposed plan. In the interest rate of 12%, the number of farmers who will continue to participate in the proposed plan will be more than the number of non-cooperative farmers, and in the interest rate of 8%, all the cooperative farmers will remain in a cooperative state without changing their behavior.

According to Figure 8, granting facilities in an interest rate of 18% cannot persuade non-cooperative farmers to participate in the proposed policies. However, out of 76 non-cooperative farmers, only five individuals were willing to change their behavior towards participation. However, with the reduction of interest rate, more farmers are encouraged to change their behavior and adopt the proposed policies. At the interest rate of 14%, the number of farmers who change their behavior and participate in the proposed policies are more than the farmers who remain in the non-cooperative state. Also, the scenario of granting facilities in an interest rate of 10% is considered as a suitable incentive to change the behavior of non-cooperating farmers and can make all non-accepting farmers accept the proposed policies.

Also, Figure 9 showed that granting facilities for the development of new irrigation technologies with the current interest rate of facilities in Iran (18%) cannot lead farmers to adopt these technologies as well as the proposed pattern based on the WEFN. Based on the obtained results, reducing the interest rate of granted facilities to 14% will make it possible to accept the proposed policies by more than half of the farmers in the present sample of study. Also, at an interest rate of 8%, all farmers are willing to adopt the proposed pattern based on the WEFN to achieve the goals of sustainable economic development and use new irrigation technologies to reduce water consumption. In general, it can be said that not considering the cooperative behavior of farmers in WSRs can result into to the failure of the proposed programs and pattern, and farmers should be encouraged to participate more in water resources management plans (Akhbari and Grigg, 2015; Farhadi et al., 2016; Mirzaei and Zibaei, 2021; Mirzaei and Azarm, 2022).

5 Conclusion

Sustainable economic development in the agricultural sector will not be achieved without paying attention to the sustainable consumption of resources such as water and energy in this sector. In this regard, the resources allocation pattern based on the WEFN can make it possible to achieve sustainable economic development in the agricultural sector. At the same time, the implementation of pattern based on WEFN in WSRs faces many challenges. The lack of water resources to improve the physical and economic productivity of water and energy as the main criteria in the WEFN will lead to farmers not adopting these patterns. Therefore, in the present study, the implementation analysis of the pattern based on the WEFN in WSRs was analyzed. For this purpose, the irrigation network of Doroodzan Dam in Fars province in Iran was selected as a WSR and the pattern based on WEFN was extracted using the combination of FAHP and TOPSIS methods. The results showed that the proposed pattern based on the WEFN will improve the physical and economic productivity of water and energy, but will not reduce water consumption. Therefore, the use of the WEFN-based pattern by farmers in the WSR requires encouraging farmers to reduce the consumption of water resources through government policy options. In this study, the policy of granting facilities at different interest rates to expand the use of new irrigation technologies was evaluated. In this regard, the ABM was used to analyze the cooperative behavior of farmers with incentive policy options. The results showed that the farmers of the studied area are resistant and would not be willing to accept the use of new irrigation technologies and the pattern based on the WEFN. This is despite the fact that reducing the interest rate of granted facilities can encourage cooperative farmers to continue this behavior and non-cooperative farmers to change their behavior. In general, it can be concluded that only the extraction of patterns based on the WEFN cannot lead to the sustainable economic development of the agricultural sector, and the evaluation of the implementation of these patterns is of great importance, especially in regions with water resource crisis. Therefore, it seems necessary to pay attention to the status of water resources in the studied agricultural regions as well as the behavior of farmers in those regions. Finally, it is suggested that for future studies, the conceptual framework of the present study should be used to apply researches in the field of WEFN. In addition, it is suggested that due to the effect of climate change on the proposed cultivation pattern and the subsequent change in the agents' behavior, in future studies, the role of this important factor in modeling the WEF nexus is addressed.

Data availability statement

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

Ethics statement

Written informed consent was obtained from the individual(s) for the publication of any potentially identifiable images or data included in this article.

Author contributions

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by [AM, NA, and MN]. The first draft of the manuscript was written by [AM] and all authors commented on previous versions of the manuscript. All authors read and approved the final 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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Does the integration of agriculture and tourism promote agricultural green total factor productivity? —Province-level evidence from China

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The integrated development of agriculture and tourism is conducive to the realization of agricultural ecological value, which will promote the green development of agriculture and improve the green total factor productivity of agriculture as well. Based on panel data in China from 2008 to 2019, the super-efficiency SBM method and the coupling coordination degree model were used to estimate the agricultural green total factor productivity (AGTFP) and the integration level of agriculture and tourism (ATL). The dynamic spatial Durbin model and threshold effect model were used to demonstrate the effects and characteristics of the agriculture and tourism integration on AGTFP. Results showed that: 1) During the study period, AGTFP and ATL increased steadily, and showed obvious spatial agglomeration characteristics; 2) The integration of agriculture and tourism will directly promote the improvement of AGTFP in the local region, and this impact has a spatial spillover effect. The direct effect in the central region in China is the strongest, and the spillover effect in the eastern region is the largest. 3) The influence of the agriculture and tourism integration on AGTFP was enhanced with the improvement of ATL, showing a threshold characteristic. From the perspective of subregion, the threshold value of ATL in the eastern region is the lowest, while the threshold value in the western region is the highest. The results of this study provide useful enlightenment for promoting the deep integration of agriculture and tourism and improvement of AGTFP so as to promote the green development of agriculture.

KEYWORDS

integration of agriculture and tourism, agricultural green total factor productivity, impact, dynamic spatial Durbin model, dynamic threshold model

1 Introduction

Since the United Nations (UN) promulgated the Declaration on the Human Environment in 1972, most countries in the world have begun to pay general attention to the problem of agricultural pollution (UNEP, 2008). This is because it not only relates to the sustainable development of agriculture but also determines the wellbeing of all humanity. In 2019, the UN Food and Agriculture Organization (FAO) released a report entitled "The State of Land and Water Resources in the World's Food and Agriculture Systems on the

Verge of Collapse". This indicated that the consumption and pollution of soil, land, and water had increased dramatically in the past ten years, and that it will be difficult to meet the food demands of nearly 10 billion people in the world in 2050 (Zhang et al., 2022). Therefore, the green and sustainable development of agriculture has attracted much attention across the world.

As a traditional agricultural country, China has made remarkable achievements in agriculture since the implementation of the reform and opening policy. Statistics show that China's total grain production increased from 430.7 million tons in 2003 to 686.53 million tons in 2022—19 consecutive years of growth. However, in the process of China's rapid agricultural modernization, problems such as excessive use of pesticides, irrational use of agricultural wastes, high consumption of fossil energy, and soil destruction have led to serious agricultural non-point source pollution and carbon emissions. According to the Second National Survey of Pollution Sources in 2021, chemical oxygen demand was 10.676 million tons, accounting for 49.77% of major pollutants discharged from agricultural production, while the amount of ammonia nitrogen was 1.415 million tons, accounting for 46.52% of major pollutants (Sun, 2022). Agricultural production has thus become a major source of pollution in China.

At the same time, as one of the world's most populous developing countries, China must feed nearly 21% of the world's population with only 9% of the world's arable land. Against this background, China's realization of green and sustainable agricultural development is a necessary choice to ensure food security and economic and social stability (Shen et al., 2019). Therefore, the central government of China has attached great importance to the green transformation of agriculture. In 2015, it first proposed the concept of green development. In 2017, the "No. 1 Document" of the Communist Party's Central Committee proposed "promoting the green production mode and enhancing sustainable agricultural development ability." In 2021, the Ministry of Agriculture and Rural Affairs formulated the 14th Five-Year Plan for National Agricultural Green Development, which clearly called for accelerating the establishment of a green, low-carbon, and circular agricultural industry system, the strengthening of the treatment of non-point agricultural source pollution, and the promotion of carbon reduction and sequestration in agriculture and in rural areas. Improving agricultural green total factor productivity (AGTFP) has become an important way of solving the dilemma of "resource–energy–environment–sustainable growth" in agriculture and of realizing agricultural green development. Therefore, the transformation of agriculture from extensive growth-driven factors to green growth driven by green total factor productivity has become a problem that must be solved for green agricultural development. Hence, it is of great significance to explore possible influencing factors for promoting AGTFP.

In recent years, promoting the integrated development of rural industries has been regarded as an important priority in the agricultural modernization of China. In 2015, the General Office of the State Council issued "Guiding Opinions on Promoting the Integrated Development of Primary, Secondary, and Tertiary Industries in Rural Areas". As an important means of rural industrial integration, the integration of agriculture and tourism has been developing rapidly. According to data released by the Ministry of Agriculture and Rural Affairs, the number of agro-tourism operators, including leisure and sightseeing farms, had reached more than 300,000, and more than 7,300 farmer cooperatives were involved in leisure agriculture or rural tourism by the end of 2019. In addition, the scale of the agro-tourism market has also been expanding. In 2019, agro-tourism received 3.2 billion tourists and generated more than 850 billion yuan in revenue, the total number of agro-tourists accounted for 53.28% of the total number of visitors in the whole domestic tourism industry, and its operating revenue accounted for 14.83% of the total operating revenue of China's domestic tourism[1]. According to data from 1,000 key rural tourism villages in China in 2022, the average contribution of agro-tourism integration to rural employment was 47.1%, and other indicators of promoting infrastructure construction were also prominent.

Agro-tourism activities are deeply affected by agricultural ecological resources, which are the prerequisite of integration (Van Zyl and Van Der Merwe, 2021). When the potential of agro-ecological resources is realized through the development of agro-tourism products, agricultural producers will then be encouraged to practice green and environmentally friendly production methods and reduce harmful inputs (Koscak, 1998; Lupi et al., 2017). In the process of integration, vertical correlation is formed between the agricultural and tourism industries, which promotes the spillover of knowledge, technology, and management among industrial-related operations (Jiang, 2022). Meanwhile, the extension of the industrial chain and the integration of the value chain also optimize the allocation of agricultural production factors, such as agricultural labor and land resources. Consequently, the efficiency of agricultural output will increase. The integrated development of agriculture and tourism, in turn, has a positive impact on agricultural green development.

Compared with other industries, cross-regional operation is an important feature of the tourism industry because of its strong mobility. China's vast territory and distinct regional variations in crop growth cycles make it possible to operate cross-regional agro-tourism. At the same time, cross-regional operations are beneficial for expanding market scale and further deepening the vertical division of labor in the whole agricultural system so that it can realize economies of scale (Pitrova et al., 2020). In addition, the seasonal nature of crop production enhances the mobility of agro-tourists, thus promoting the efficiency of information and technology exchange between regions. Therefore, the impact of agro-tourism integration on agricultural green development may have a spillover effect.

In the process of the integration of agriculture and tourism, agriculture's ecological premium is realized. However, in the early stages of this integration, the agricultural ecological premium is not so high so that agricultural production is mostly carried out in traditional production modes (Hu and Zhong, 2019). At this stage, agricultural production mainly aims at improving agricultural production efficiency and rarely actively reduces the input of harmful environmental factors such as fertilizers and pesticides. Therefore, the promotion effect of low-level integration on AGTFP

1 Data of 2020–2022 were not taken into account due to impact of COVID-19 pandemic.

is not so significant. With more in-depth development of this integration, agriculture's ecological premium will be more fully realized (Jiang, 2022). This can encourage agricultural producers to reduce harmful inputs and to adopt green production methods. They will thus pay increasing attention to the green and sustainable development of agriculture to obtain a higher agricultural–ecological premium. Therefore, increased agriculture and tourism integration has an enhanced positive effect on AGTFP.

Existing studies have paid little attention to the impact of agriculture–tourism integration on the green development of agriculture. There are few empirical studies on the effect of agriculture and tourism integration on AGTFP, especially on its spillover and non-linear effects. Therefore, the main purposes of this paper are to 1) assess the level of agricultural green total factor productivity (AGTFP) accurately, based on the super efficiency SBM method with provincial data from China; 2) measure the integration level of agriculture and tourism (ATL) with the coupling coordination degree model to better identify the linkage of agriculture and tourism; 3) demonstrate the spillover and non-linear effects of agriculture–tourism integration on AGTFP based on the dynamic spatial model and threshold model respectively; 4) propose specific policy recommendations for improving agriculture–tourism integration to promote AGTFP. The study also makes more marginal contributions. First, it demonstrates the impact of the integration of agriculture and tourism on AGTFP with empirical analysis, providing a new perspective for exploring factors which may affect agricultural green development. Second, it focuses on the environmental effect of agriculture–tourism integration—while most studies concern its economic impacts—and thus expands the scope of research on the effect of this integration. Third, the spatial spillover and non-linear effects of agriculture–tourism integration on AGTFP are demonstrated by using the dynamic spatial Durbin and dynamic threshold models, which can more scientifically reveal the impact of agriculture–tourism integration on AGTFP. Additionally, the dynamic characteristics of AGTFP are considered in the estimation of the impact of agriculture–tourism integration on AGTFP, thus effectively avoiding the endogeneity problem.

The remaining parts of this paper are structured as follows. Section 2 reviews the literature on agro-tourism integration and AGTFP and also constructs a theoretical framework. Section 3 provides model selection, variable measures, and data descriptions. Section 4 presents the empirical results and discusses them in detail. Finally, this paper proposes precise policy implications for promoting AGTFP based on the results of the empirical analysis.

2 Literature review and theoretical framework

2.1 Literature review

2.1.1 The integration of agriculture and tourism

There is a strong linkage between tourism and agriculture (Ammirato et al., 2020). Tourism activities create a demand for tourism products, thus determining the production of agricultural products and food in the process of tourism consumption (Ristić et al., 2019). On the other hand, agricultural production processes and seasonal characteristics affect the content of tourism supply (Sanches-Pereira et al., 2017; SoleimannejadAlibaygi and Salehi, 2021). Given the strong linkage between tourism and agriculture, increasing attention has been given to agriculture–tourism integration (Gilbert and Hudson, 2000; Streifeneder, 2016; Ristić et al., 2019). Based on symbiosis theory, Chen (2014) argued that the integrated development of tourism and agriculture is the internalization of the inter-industry division of labor and the sharing of products, markets, and resources by the two industries, thus realizing their developing symbiosis. Nie and Fan (2019) argued that such integration is a process in which the internalization is the inter-industrial division of labor and the sharing of products, markets, and resources, and that it is driven by market demand, economic growth, and competition.

Increasing attention has been paid to the impact of the integrated development of agriculture and tourism on the rural economy, society, and the environment. In terms of its economic effects, research has found that establishing effective links between agriculture and tourism not only leads to new market space and consumer demand but also promotes high-quality tourism and agricultural products (Tew and Barbieri, 2012; Testa et al., 2019). Although the agricultural products required by tourism are only a small part of total agricultural productivity, they still play a key role in ensuring the quality of these products (Valdivia and Barbieri, 2014). Many scholars have empirically tested the effect of agriculture–tourism integration on rural and regional economic growth (Van Sandt and Thilmany Mcfadden, 2016). In terms of its social effects, they argue that the development of agro-tourism can provide economic incentives and stability for farmers and improve the quality of life of rural populations in mountainous areas, thus meeting challenges of population migration and economic change (Dax et al., 2019). This is also conducive to strengthening urban–rural links and preserving natural and cultural heritage (Streifeneder, 2016). In terms of its environmental effects, scholars hold different views on the ecological effect of agriculture–tourism integration. Some argue that tourism provides agriculture with another source of income, which is conducive to sustainable agricultural development. The development of agro-tourism draws part of the agricultural labor force and provides funds for farmers to adopt innovative technologies such as fertilizers, allowing them to expand production without increasing tillage frequency or clearing new land to indirectly reduce environmental degradation (Guaita Martínez et al., 2019). However, drawing labor from agriculture may also lead to a loss of farmers with land management skills, leading to deterioration in the agricultural ecological environment (SoleimannejadAlibaygi and Salehi, 2021). Overall, above studies have come to opposite conclusions, so whether the integration of agriculture and tourism can promote AGTFP needs to be further verified.

2.1.2 Agricultural green total factor productivity

The sustainable and high-quality development of agriculture depends, on one hand, on the continuous increase of labor, machinery, equipment, land, and other factors of production, and on the improvement of the efficient use of production factors on the other hand. Agricultural total factor productivity is one of the main

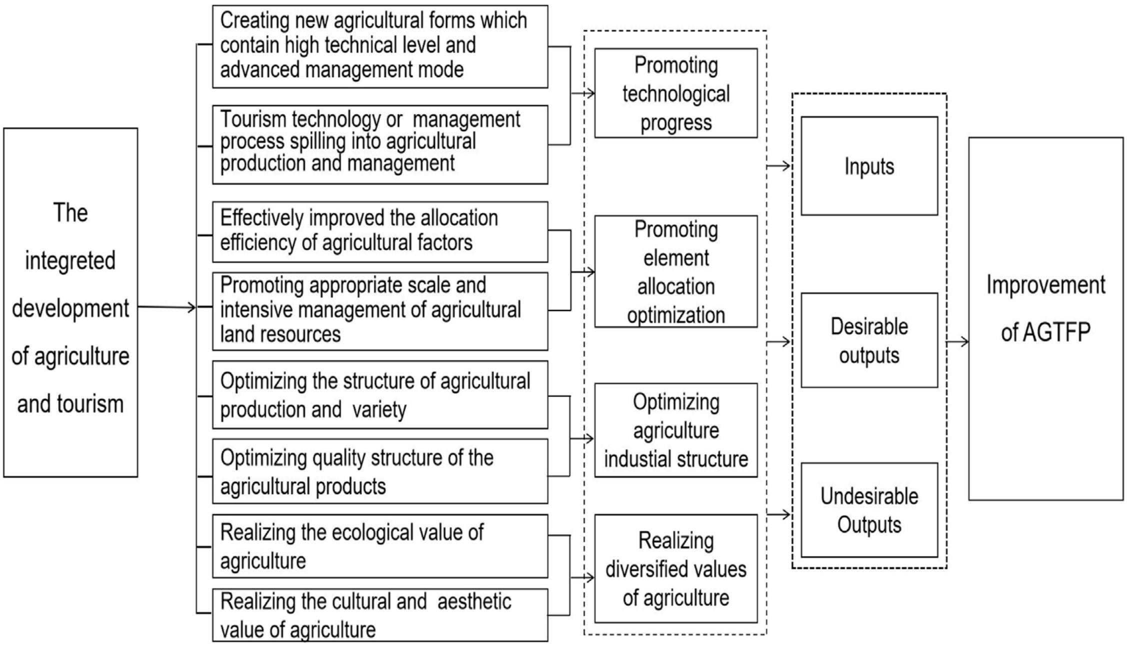

FIGURE 1
Impact mechanism of agriculture–tourism integration on improving AGTFP.

indicators for measuring the efficiency of production factors. As environmental pollution becomes more and more serious, the addition of environmental and resource factors to the traditional agricultural total factor productivity framework has become an academic research hotspot, begetting the concept of agricultural green total factor productivity (AGTFP). Research on AGTFP is mainly done into the following aspects.

The DEA and SFA methods are widely used for the measurement of AGTFP (Adetutu and Ajayi, 2020; Chen et al., 2021; Wang et al., 2023). Compared with SFA's parametric method, DEA is non-parametric, does not need specific production functions and inefficiency items in advance, and is less subject to subjective influence (Gong, 2020). Emrouznejad and Yang (2018) reviewed the literature from 1978 to 2016 and found that DEA has high applicability in measuring agricultural production efficiency. In the early literature, angular and radial DEA models were used to measure agricultural total factor productivity, which required the selection of input or output angles of the model and required these to change in the same proportion, which was inconsistent with actual production. To avoid this problem, the slacks-based measurement (SBM) model proposed by Tone (2001) was used to evaluate AGTFP. However, when there are more than two effective units in the same period, the SBM standard efficiency model cannot sort them. So Tone (2002) further proposed the super efficiency SBM model. When considering undesirable outputs, the SBM super efficiency model incorporating undesirable output is commonly used to measure AGTFP.

With the improvement of AGTFP measurement methods, scholars began to pay attention to the influencing factors of AGTFP. According to Sheng et al. (2020), agricultural economic development level, agricultural production structure, and agricultural technology levels are important factors affecting AGTFP (Sheng et al., 2020). Regional characteristics also affect the growth of AGTFP. Gao and Niu (2018) observed that different regional economic development factors in China lead to regional differences in AGTFP. Other studies have found that agricultural tax reduction (Liang and Long, 2015), rural financial development (Li, 2021), environmental regulation (Huang et al., 2021), and agricultural informatization (Gao and Niu, 2018) can promote AGTFP, while urbanization and agricultural trade could inhibit it (Liang and Long, 2015). However, few studies have analyzed the factors that influence AGTFP from the perspective of industry integration. Only Wang et al. (2022) have tested the linear influence of agro-tourism industry agglomeration on AGTFP, but without considering the possible spatial spillover and non-linear characteristics of this influence.

2.2 Theoretical framework

The integration of agriculture and tourism refers to the process of developing agricultural tourism resources and managing agricultural tourism products by relevant stakeholders to maximize economic, social, and ecological effects under certain rural economic and social backgrounds. Therefore, the integration of agriculture and tourism not only plays a role in promoting the development of the rural economy but also has an impact on improving AGTFP, which is mainly reflected in the following aspects (Figure 1).

First, this integration promotes progress in agricultural technology. Agriculture–tourism integration promotes the spatial agglomeration of business units and promotes the flow of talent and technological interaction. Advanced technology and management experience in tourism enterprises also share their knowledge, technology, and management skills with related or cooperative agricultural operation subjects so that the technical level of agricultural production and operation can be improved (Ristić et al., 2019).

Second, the integration promotes optimal resource and element allocation. Under traditional agricultural management, the function of agricultural resources and products is relatively simple, and the application scope is relatively narrow. The allocation framework of agricultural factors is mainly reflected in the level of limited capital, abundant land, and primary labor resources, which makes for a relatively inefficient allocation of agricultural production factors. In the process of agriculture–tourism integration, the capital, technology, talents, information, and management elements of the two industries realize a market-oriented flow and full interaction, thus promoting a higher optimal allocation of various production factors and effectively improving the allocation efficiency of agricultural factors (Fleischer and Tchetchik, 2002; Ammirato et al., 2020).

Third, this integration promotes the optimization and upgrading of the agricultural industrial structure. The integral development of agriculture and tourism has enriched the development of rural tourism and created a large number of rural tourism products or service formats with rich content (Hsu et al., 2013). For example, a variety of new business formats have appeared in practice, such as national agricultural parks, leisure farms, rural camps, rural museums, citizen agricultural parks, and rural homestays. Driven by demand, the adjustment of the allocation of agricultural production factors has led to the optimization of the quality and variety of the agricultural production (Amsden and McEntee, 2011).

Fourth, integration contributes to the realization of diversified values of agriculture, resulting in increased agricultural output. It is helpful to expand the tourism function of agricultural resources and promote appreciation of the value of agricultural products, the natural ecology, and human resources as tourism products (Fleischer and Tchetchik, 2002). Therefore, the integration of agriculture and tourism effectively expands income growth in agricultural production and management activities. Moreover, agriculture–tourism integration contributes to the cultivation of agricultural products and regional brands, thus enhancing the popularity and reputation of agricultural products; this plays an important role in enhancing the added value of agricultural product sales (Pillay and Rogerson, 2013).

Accordingly, we propose the following research hypothesis: "The integrated development of agriculture and tourism has a positive effect on the improvement of AGTFP."

3 Methods and materials

3.1 The Super-SBM method

The super efficiency SBM model (super-SBM) is used in this study to calculate China's AGTFP. Compared with the radial and angular DEA and SBM models, super-SBM can effectively evaluate and rank multiple fully effective decision units (Tone, 2002). Here, 360 decision-making units (DUS) from 30 provinces from 2008 to 2019 were used. If the kth decision unit ($j = 1, 2, \ldots, n$) has input vectors $x \in R^M$, expected output vector $y^g \in R^{s_1}$, undesired output vector $y^g \in R^{s_2}$, respectively. Also, define the matrix $X = [x_1, x_2, \cdots, x_n] \in R^m \times n$, $Y^g = [y_1^g, y_2^g, \cdots y_n^g] \in R^{s_1} \times n$, $Y^b = [y_1^b, y_2^b, \cdots y_n^b] \in R^{s_2} \times n$. For the measured decision unit k, in Formula 1:

$$\min \rho = \frac{1 + \frac{1}{m}\sum_{i=1}^{m}\frac{S_i^-}{x_{ik}}}{1 - \frac{1}{s_1 + s_2}\left(\sum_{r=1}^{S_1}\left(S_r^g/y_{rk}^g\right) + \sum_{t=1}^{S_2}\left(S_t^b/y_{tk}^b\right)\right)}$$
$$s.t. \sum_{j=1, j\neq k}^{n} x_{ij}\lambda_j - s_i^- \leq x_{ik} \tag{1}$$
$$\sum_{j=1, j\neq k}^{n} y_{rj}\lambda_j + s_r^g \geq y_{rk}^g$$
$$\sum_{j=1, j\neq k}^{n} y_{tj}\lambda_j - s_t^b \leq y_{tk}^b$$
$$\lambda \geq 0, s^g \geq 0, s^b \geq 0, s^- \geq 0,$$

where λ is the weight vector, and s_i^-、 s_r^g、 s_t^b are slack variables. $\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{ik}}$ represents the average inefficiency of inputs, and $\frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1} S_r^g/y_{rk}^g + \sum_{t=1}^{s_2} S_t^b/y_{tk}^b\right)$ represents the average inefficiency of outputs. ρ is the efficiency value of a decision unit and can be greater than 1, so the effective decision unit can be distinguished.

3.2 The coupling coordination degree model

In an open industrial system, different industries may lead to industrial coupling due to resource complementarity, which makes the industrial system evolve toward an advanced and orderly state (Nie, 2019). Chen (2014) believes that although the concepts of industrial coupling and industrial convergence are different, industrial coupling reflects the dynamic process of gradual integration between industries, while industrial convergence reflects the internal interaction and correlation between industries. However, the two have the same effect and the deep-level theories are similar. Many scholars use the coupling coordination degree model (CCDM) to evaluate the degree of industrial integration. For example, Su (2020) used it to measure the integration level of producer services and manufacturing in China from 2005 to 2018. Xu and Chen (2020) built an evaluation index system of coupling coordination for the development of the sports and tourism industries based on CCDM and discussed the comprehensive level and coupling coordination degree of these industries in 31 provinces in mainland China. Wang (2018) calculated the integration degree of agriculture and tourism based on this model. In general, CCDM has good applicability and is also used to construct the integration level measurement model of the agriculture and tourism industries in this study. The construction process of the CCDM for the agriculture and tourism industry is as follows:

① Standardize the data of the evaluation index:

When the evaluation index is a positive index:

$$y_{ij} = \frac{x_{ij} - \min x_j}{\max x_j - \min x_j}. \tag{2}$$

When the evaluation index is a negative index:

$$y_{ij} = \frac{x_{\max} - x_j}{\max x_j - \min x_j}. \tag{3}$$

② Calculate the information entropy:

$$h_j = -k\sum_{i=1}^{m} p_{ij} Inp_{ij}\left(\text{Where } p_{ij} = \frac{y_{ij}}{\sum_{i=1}^{m} y_{ij}}, k = \frac{1}{Inm}\right). \tag{4}$$

Define the weight of the *jth* indicator as

$$w_j = \frac{1 - h_j}{\sum_{j=1}^{n}\left(1 - h_j\right)}\left(\text{Where } w_j \in [0,1], \text{and} \sum_{j=1}^{n} w_j = 1\right). \tag{5}$$

③ Calculate the development level of the agriculture and tourism industries. The agricultural comprehensive evaluation function was determined and established according to the linear weighting method:

$$A(x) = \sum_{j=1}^{n} w_j M_{ij.} \tag{6}$$

In Formula 6, j is the number of evaluation indexes of agricultural development level, w_j is the weight of indexes, and M_{ij} is the standardized value of the *jth* agricultural index in the *ith* year. The higher the value of *A(x)*, the higher the level of comprehensive agricultural development will be, and *vice versa*. Similarly, the comprehensive evaluation function of tourism industry is established

$$T(y) = \sum_{i=1}^{n} w_j N_{ij.} \tag{7}$$

The interpretation of each indicator in Formula 7 is similar to that in Formula 6. The larger the value of *T(y)*, the higher the development level of tourism will be, and *vice versa*.

④ The CCDM of agriculture and tourism industry is established as follows:

$$C = \sqrt[2]{\frac{A(x)\cdot T(y)}{\left(A(x) + T(y)\right)^2}}. \tag{8}$$

$$D = \beta \cdot A(x) + \gamma \cdot T(y). \tag{9}$$

$$ATL = U = \sqrt{C \cdot D}. \tag{10}$$

In Formula 10, C is the coupling degree, $C \in [0,1]$. The greater the value of C, the more ideal the degree of the integration of the two industries will be, and *vice versa*. The coupling degree C only reflects the interaction and cross state of the agriculture and tourism industries and cannot accurately reflect their actual integration and development level. In order to avoid the illusion that the development level of the two subsystems is not high but the coupling degree of them is, the coupling coordination degree U is used to represent the integration level of agriculture and tourism (ATL). The larger the U value, the better the coupling coordination will be. Generally speaking, the greater the value of coupling coordination degree, the higher the degree of integration between industries will be (Su, 2020). In Formula 9, β and γ are undetermined coefficients, and D is the comprehensive coordination index of the agriculture and tourism industries. In view of the interactional relationship between the agriculture and tourism industry system in the process of integration, this paper follows the view of Wang (2018), making $\beta = \gamma = 0.5$.

3.3 Empirical models

3.3.1 The spatial econometric model

3.3.1.1 Global Moran's *I* Index

According to the first law of geography, regional economy is an open system. There are various kinds of material and immaterial connections between regions, which lead to mutual influence and interdependence among regions, thus leading to mutual influence and interdependence. The economic growth of a region no longer only depends on its initial conditions but also closely on the economic activities of neighboring regions (Mitchell et al., 2012). Therefore, an analysis of the impact of agriculture–tourism integration on AGTFP without considering spatial factors may lead to biased results and even overestimate the impact. Whether it is necessary to introduce spatial effect into the regression model depends on the existence of spatial correlation of economic variables. Whether there exist spatial effects among economic variables can be examined by the global *Moran's I* index, which is defined as

$$Moran'I_{global} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{m} W_{ij}\left(Y_i - \bar{Y}\right)\left(Y_i - \bar{Y}\right)}{S^2\sum_{i=1}^{n}\sum_{j=1}^{m} W_{ij}}. \tag{11}$$

In the aforementioned formula, Y_i *and* Y_j represent the observed value of the integration level of agriculture and tourism (ATL) or agricultural green ecological efficiency ($AGTFP$) in region i and j, respectively. W_{ij} is the spatial weight matrix. The value of Moran's I index belongs to [−1, 1]. When the index is greater than 0, it indicates that Y has a positive spatial correlation. When the index is less than 0, it has negative spatial correlation. Otherwise, there is no spatial correlation.

3.3.1.2 The Dynamic Spatial Durbin Model

Spatial models mainly include spatial lag models (SLMs) and spatial error models (SEMs) (Anselin, 1998). If both the explained and the explanatory variables are spatially dependent, it is the spatial Durbin model (SDM). In view of the spatial dependence of the explained variable $AGTFP$ and explanatory variable ATL, the spatial Durbin model is constructed in this study. Because AGTFP is also affected by the previous phase state, the term lagging one stage ($AGTFP_{i,t-1}$) is included in the equation, which can effectively solve the endogenous problem of the model. The dynamic spatial Durbin model is constructed as follows:

TABLE 1 Measuring indicators of AGTFP.

Type of variables		Evaluation of indicator	Unit
Input indicators	Input of labor	Number of people employed in agriculture, forestry, husbandry, and fishery	10 thousand people
	Input of land	Crop sown area and aquaculture area	1 thousand hectares
	Input of capital	Total power of agricultural machinery	1 million kw
		Application amount of converted agricultural chemical fertilizer	10 thousand tons
		Pesticide usage	10 thousand tons
		Agricultural film usage	Ton
	Input of energy	Agricultural diesel usage	10 thousand tons
		Agricultural electricity consumption	Kw·h
	Input of water	Agricultural water consumption	100 million m^3
Output indicators	Desirable output	Total output value of agriculture, forestry, husbandry, and fishery	100 million CNY
	Undesirable output	Agricultural carbon emission	10 thousand tons
		Agricultural pollution composite index	—

$$AGTFP_{it} = \alpha_0 + \tau AGTFP_{i,t-1} + \rho\sum_{j=1}^{n} W_{ij}AGTFP_{jt} + \beta X_{it} + \theta\sum_{j=1}^{n} W_{ij}X_{jt} + \mu_i + v_t + \varepsilon_{it}. \quad (12)$$

In the aforementioned formula, $AGTFP_{it}$ and X_{it} represent the explained and the explanatory variables (including control variables) respectively. The subscripts i and t denote the province and year, respectively. ρ is the spatial correlation coefficient, and W_{ij} is the spatial weight matrix. τ, β, γ, θ, and ξ are the parameters to be estimated, u_i is the spatial effect, v_t is the time effect, and ε_{it} is the spatial error term. The spatial weight matrix includes two types: ① The geographical distance spatial weight matrix ($W1$), which is usually calculated by the reciprocal of the square of the actual geographical distance between the two regions:$W_{ij} = 1/d_{ij}^2\,(i \neq j)$. d_{ij} is represented by the direct distance between the two provincial capitals. $W1$ is selected as the benchmark spatial weight matrix. ② The economic geographic nested spatial weight matrix ($W2$) is calculated by the following formula: $W_{ij} = 1/|\bar{Y}_i - \bar{Y}_j + 1|e^{-d_{ij}}$, $(i \neq j)$. $\bar{Y}_i$ and $\bar{Y}_j$ represent the per capita GDP of the ith and jth province, respectively. d_{ij} is also represented by the direct distance between the two provincial capitals. $W2$ is used for model robustness analysis.

3.3.2 The dynamic panel threshold model

With the continuous deepening of agriculture–tourism integration, the ecological premium of agriculture will be fully realized, further strengthening the green production behavior of producers and thus further improving AGTFP. The influence of agricultural and tourism integration on AGTFP may be enhanced with the improved integration. Therefore, the influence of agriculture–tourism integration on AGTFP may have a non-linear relationship, so we take ATL as the threshold variable to test this non-linear relationship. As well as considering that AGTFP has the characteristics of dynamic persistence, this paper included AGTFP with one stage lag as an explanatory variable. Due to the lack of mature methods to combine the spatial econometric model and the threshold regression model, the common dynamic panel threshold regression model is finally established thus:

$$\begin{aligned} AGTFP_{it} =& \alpha_0 + \rho AGTFP_{i,t-1} + \beta_{11}ATL_{it} \times I(ATL_{it} \le \theta_1) + \beta_{12}ATL_{it} \\ & \times I(\theta_1 < ATL_{it} \le \theta_2) + \cdots + \beta_{1,n}ATL_{it} \times I(\theta_{n-1} < ATL_{it} \le \theta_n) \\ & + \beta_{1,n+1}ATL_{it} \times I(ATL_{it} > \theta_n) + \sum_{k=1}^{n}\lambda_k C_{it,k} + \mu_i + \xi_{it} \end{aligned} \quad (13)$$

Among these, θ_1, θ_2, . . ., and θ_n are threshold values, there were n+1 threshold intervals, β_{11}, β_{12}, . . ., and $\beta_{1,n}$ are regression coefficients under different threshold intervals. $I(\cdot)$ is the indicative function. t-1 means one phase lag behind, and other indicators are defined by reference to Formula 12.

3.4 Variable selection

3.4.1 Explained variable

When the super-SBM model is used to calculate the AGTFP considering undesirable output and expected output, the undesirable output and the input indexes should be determined first.

(1) Input indicators. According to Guo and Liu (2021), a measurement system of agricultural input indicators integrating "resources, energy, environment, and economy" must be constructed (Table 1). As for the importance of variable indicators, the entropy weight method is adopted to assign weights to all indicators to reflect the importance of the indicators. Agricultural input factors include labor, land, capital, water resources, and electrical energy, which are the necessary conditions for agricultural development. *Labor input* is measured by the number of people employed in agriculture,

TABLE 2 Indicators for measuring the integration level of agriculture and tourism.

Elements	Indicators	Attribute	Data sources
Characteristic agriculture	Number of geographical indications of agricultural products	+	Ministry of Agriculture and Rural Affairs
	Number of brands in the "One Brand in One Village" Project	+	
	Output value of characteristic agricultural products (1 billion CNY)	+	
	Number of advantaged agricultural products with local characteristics	+	
	Area of fruit orchards (1 thousand hectares)	+	China Rural Statistical Yearbook
Rural tourism	Number of A-level scenic spots	+	Ministry of Culture and Tourism
	Number of key villages and towns for rural tourism in China	+	
	Number of demonstration counties for leisure agriculture and rural tourism	+	
	Revenue of rural tourism and leisure agriculture (1 billion CNY)	+	
	Number of famous towns and villages of national characteristic landscape tourism	+	

forestry, husbandry, and fisheries at the end of the year. *Land input* is measured as the sum of the crop-sown area and aquaculture area. The selection of capital input variables differs from the existing literature, which mainly considers the radial and non-radial relationships between agricultural input and output. *Chemical fertilizer*, *machinery*, *pesticides*, *agricultural film,* and *diesel oil* are selected as capital inputs. Compared with the existing literature, draft animals were not included because the sample study period of this study was 2008–2019 after the cancellation of agricultural subsidies by the United Nations. During this period, the agricultural mechanization level was gradually improved, which had a strong substituting effect on draft animals. *Water resource input* is measured by total agricultural water use. *Agricultural electricity consumption* represents the input of electrical energy.

(2) Output indicators. The desirable output indicator is represented by *the total output value of agriculture, forestry, husbandry, and fisheries* and is adjusted to 2008 prices. Agricultural undesirable outputs mainly refer to various environmental pollution emissions, including chemical oxygen demand in water, total nitrogen and total phosphorus loss, carbon dioxide emissions in agricultural production, and ineffective pesticide utilization and agricultural film residues in soil. Among these, water pollution and soil pollutant residues were calculated by unit investigation and evaluation method (Chen et al., 2006). In addition, in order to adapt to the required ratio between the input–output index and the decision-making unit of the DEA model, this paper combined the variables of water and soil pollution into the comprehensive index of agricultural pollution by using the entropy weight method based on Jiang and Wang, (2019). At the same time, in order to further consider the greenhouse gas emissions caused by various production factors in agricultural production, the carbon emissions of four agricultural production activities that lead to agricultural carbon emissions were calculated according to West and Marland (2002). In this paper, the agricultural pollution composite index and agricultural carbon emissions treated by the entropy weight method are included in the super-SBM model as non-expected output to measure AGTFP. All indicators for measuring AGTFP are shown in Table 1.

3.4.2 Explanatory variable

As discussed in the literature review, the integrated development of agriculture and tourism refers to the process of forming a distinctive brand of agriculture and tourism based on a certain theme or regional characteristics of agricultural resources in combination with agricultural resource endowment. Characteristic agricultural tourism brands such as agricultural tourism towns, key tourism villages, leisure agriculture, and rural tourism demonstration counties formed around agricultural geographic indication products can best reflect the characteristics and elements of the integrated development of agriculture and tourism. Therefore, this study used published data that can represent the development level of the agricultural tourism industry to replace the general indicators in the statistical yearbook, such as tourism income and agricultural output value, so as to make the measured integration level of agriculture and tourism more targeted and reasonable. Based on Yang et al. (2022), five indicators were selected to measure the development level of characteristic agriculture and another five to measure the development level of rural tourism. All indicators are shown in Table 2.

3.4.3 Control variables

Since many other factors affect AGTFP, this paper selected several control variables to alleviate, as much as possible, the endogeneity problem caused by missing variables: 1) *Agricultural industrial structure* (*AIS*), expressed as the proportion of the added value of the plantation industry in the added value of agriculture, forestry, animal husbandry, and fishery. Generally speaking, the higher the proportion of the planting industry, the higher the degree of agricultural production agglomeration—*AIS* is thus expected to have a positive impact on AGTFP. 2) *Income distribution* (*INC*), expressed as the ratio of urban *per capita* disposable income to rural *per capita* net income. The greater the income gap between urban and rural residents often means that a regional government does not pay enough attention to agricultural development, or that agricultural resource endowment is poor. Moreover, in order to increase income, agricultural producers will choose to ignore the externalities in the process of agricultural production. Therefore, the impact of income distribution on AGTFP may be negative. 3) *Trade dependency* (*TRD*), expressed as the ratio of the total amount of regional agricultural

TABLE 3 Relevant variables and descriptions.

Variable	Variable name	Unit	Calculation method	Data source
Explained variable	*AGTFP*	_	Calculated by super-SBM method	Shown in Table 1
Core explanatory variable	*ATL*	_	Calculated by coupling coordination degree model	Shown in Table 2
Control variable	Agriculture industrial structure (*AIT*)	%	Represented by proportion of the added value of plantation industry in added value of agriculture, forestry, animal husbandry, and fishery	China Rural Statistical Yearbook
	Disaster-affected degree (*DIS*)	%	Represented by proportion of disaster-affected area in total sown area of crops	
	Income distribution (*INC*)	%	Represented by ratio of urban *per capita* disposable income to rural *per capita* net income	China Statistical Yearbook
	Trade dependency (*TRD*)	%	Represented by ratio of the total amount of regional agricultural imports and exports to gross agricultural product	China Agricultural Yearbook and China Agricultural Trade report
	Educational level of the labor force (*EDU*)	%	Represented by average years of schooling	China Population and Employment Statistical Yearbook

TABLE 4 Description of variables in the specification model.

Variables	Observations	Mean	Median	Std. Dev	Max	Min
AGTFP	360	1.0933	1.074	0.069	1.367	0.876
ATL	360	0.656	0.651	0.078	0.783	0.454
AIT	360	0.569	0.447	0.585	0.769	0.304
INC	360	2.916	3.154	0.083	5.113	1.854
TRD	360	0.311	0.325	0.008	0.364	0.010
DIS	360	0.244	0.238	0.157	0.872	0.000
EDU	360	7.554	7.512	0.839	9.211	4.895

imports and exports to the gross agricultural product. The agricultural trade situation will affect the regional AGTFP by affecting the income of agricultural producers and the agricultural production environment; the direction of its influence is unknown. 4) *Disaster-affected degree* (*DIS*) is expressed by the proportion of a disaster-affected area in a total sown area of crops. Generally speaking, the higher the degree of disaster, the greater the damage to farmers' income and the production environment, which is expected to negatively affect AGTFP. 5) *The educational level of the labor force* (*EDU*) is represented by the average years of schooling based on the practice. By using the calculation method of Liu and Xu (2010), the average years of schooling for residents with primary, middle, high, secondary, and tertiary education were set as 6, 9, 12, and 16 years, respectively. Thus, EDU = prim × 6 + midd × 9 + high × 12 + univ × 16, where prim, midd, high, and univ represent the proportion of residents with education above primary, middle, high, and university in the population aged 6 and above in the region, respectively. Generally speaking, the higher the educational level of agricultural producers, the more beneficial this will be to mastering production skills and the rational use of chemical factors; thus, *EDU* will theoretically have a positive effect on AGTFP. All relevant variables and their descriptions are shown in Table 3.

3.5 Data sources and descriptive statistics

The empirical analysis is based on panel data from 30 provinces in China from 2008 to 2019. Hong Kong, Macao, Taiwan, and Tibet Autonomous Region are excluded due to missing data. Since the beginning of 2020, the tourism industry has been significantly impacted by the COVID-19 epidemic. Therefore, data from 2020 to 2022 are not considered in the study period. The data sources are mainly drawn from China Rural Yearbooks, the China Statistical Yearbook, and the China Tourism Statistical Yearbook. In addition, the National Bureau of Statistics, the Ministry of Culture and Tourism, the Ministry of Agriculture, and official provincial websites are used as supplementary sources of data. All data measured in monetary units are deflated based on constant price levels of 2008. R and GeoDa software were used for quantitative analysis and model estimation. The results of descriptive statistics for each variable are shown in Table 4.

3.6 Characteristics of AGTFP and ATL in China

According to results of super-SBM to calculate AGTFP, the change trend of annual mean AGTFP in 30 provinces and four

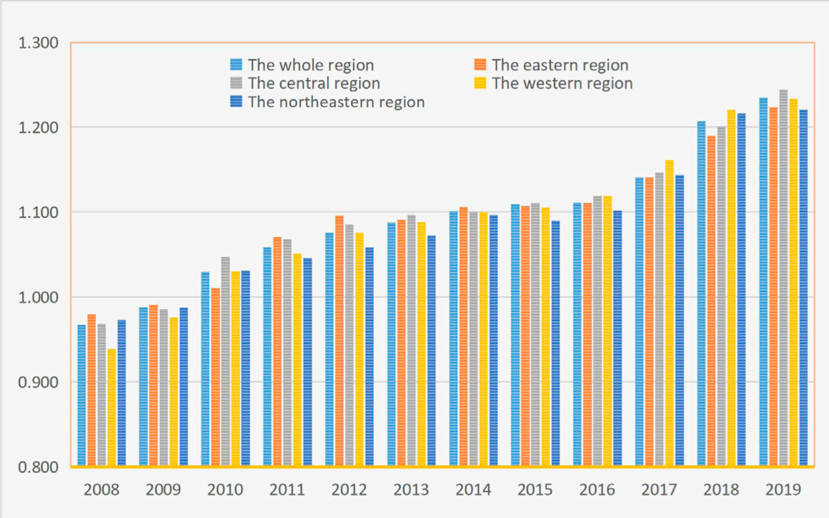

FIGURE 2
Development trend of AGTFP in China from 2008 to 2019.

TABLE 5 Change trends of annual average of ATL in different regions.

Year	Whole region	Eastern region	Central region	Western region	Northeast region
2008	0.572	0.609	0.563	0.564	0.541
2009	0.593	0.612	0.586	0.579	0.563
2010	0.611	0.631	0.597	0.611	0.592
2011	0.631	0.655	0.629	0.627	0.602
2012	0.648	0.670	0.632	0.631	0.611
2013	0.655	0.684	0.634	0.642	0.621
2014	0.661	0.687	0.655	0.651	0.633
2015	0.674	0.691	0.671	0.666	0.647
2016	0.693	0.703	0.678	0.671	0.658
2017	0.699	0.715	0.681	0.676	0.665
2018	0.714	0.732	0.708	0.683	0.678
2019	0.722	0.743	0.721	0.699	0.688
Mean value	0.656	0.678	0.646	0.642	0.625

regions from 2008 to 2019 is shown in Figure 2. The annual mean of AGTFP in the whole region fluctuated roughly between 0.967 and 1.235 from 2008 to 2019, reaching its maximum in 2019. In recent years, the central government has attached great importance to environmental protection and targeted agricultural pollution. Governments at all levels have thus formulated a series of control measures to effectively promote agricultural clean production technology. Overall, China's AGTFP showed an upward trend from 2008 to 2019, with an average annual growth rate of 2.26%. For four different regions, AGTFP is greater than 1 in most years. The average annual growth rates of AGTFP in the eastern, central, western, and northeastern regions during the study period were 2.06%, 2.31%, 2.53%, and 2.10%, respectively. The growth rate of AGTFP in the western region is higher than in other regions, which may be due to the long-term undeveloped level of agricultural production there. In recent years, with the introduction of advanced green production technology, AGTFP in this region has rapidly grown.

Meanwhile, ATL was measured with panel data based on the coupling coordination degree model. Results show that the mean value of ATL in eastern China is the highest, while the mean value of ATL in western and northeastern China is relatively lower among the four regions (Table 5). From Table 5, we can see that the average of ATL in the eastern region is the highest among all regions over the

TABLE 6 Global Moran's I values of ATL and AGTFP 2008–2019.

Global Moran's I values of ATL						Global Moran's I values of AGTFP					
Year	Moran's I	*p*-value	Year	Moran's I	*p*-value	Year	Moran's I	*p*-value	Year	Moran's I	*p*-value
2008	0.233**	0.041	2014	0.269**	0.022	2008	0.321*	0.078	2014	0.383*	0.075
2009	0.234***	0.002	2015	0.273**	0.034	2009	0.334*	0.019	2015	0.401*	0.083
2010	0.247*	0.085	2016	0.271***	0.008	2010	0.331*	0.096	2016	0.415*	0.064
2011	0.248*	0.097	2017	0.269***	0.003	2011	0.345**	0.045	2017	0.411**	0.019
2012	0.253**	0.039	2018	0.284***	0.004	2012	0.363**	0.021	2018	0.422***	0.004
2013	0.258***	0.002	2019	0.289***	0.008	2013	0.371**	0.044	2019	0.434***	0.001

Note: *, **, and *** respectively denote significance at confidence levels of 10%, 5%, and 1%, respectively.

study period. The annual average of *ATL* of the whole research region continuously improved over time, with average annual growth rates of 2.14%. The average annual growth rates of ATL in eastern, central, western, and northeastern regions during the study period were 1.83%, 2.29%, 1.97%, and 2.22%, respectively. The growth rate of ATL in the central region is higher than in other regions. The integration of agriculture and tourism is an important form of rural industry integration that can promote rural economic growth and rural revitalization. Thus, it is also strongly supported by the government. With the strong support of an integrated development policy, the integration level of agriculture and tourism in different regions showed an obvious growth trend.

4 Results and discussion

4.1 Results of spatial Durbin model and analysis

4.1.1 Global spatial autocorrelation analysis

From Table 6, it can be seen that the global Moran' I values of ATL and AGTFP over the years are positive, and all pass the significance test, indicating that ATL and AGTFP have significant spatial correlation. From the perspective of time, the mean values of the global Moran' I values of ATL and AGTFP basically increased year by year. It can be concluded that the spatial agglomeration trend of the integrated development of agriculture and tourism and the green development of agriculture are constantly strengthening.

4.1.2 Identification of spatial models

First, the multi-collinearity and stationarity of variables were tested. Variance inflation factor (VIF) results show that the maximum value of variable VIF is less than 6, with no multi-collinearity. According to Im et al. (2003), LLC, Fisher-ADF, and PP-Fisher are used to test the stationarity of the time series, with the results showing that the null hypothesis was rejected at the significance level of 5%, and that the original series is stationary.

Second, the optimal form of the spatial panel model is identified. The aforementioned spatial auto-correlation test shows that both AGTFP and ATL have strong spatial correlation characteristics, so spatial factors should be considered when studying the relationship between them. We then followed the "two-step method" proposed by Elhorst (2003) to determine the appropriate spatial econometric model. The first step was to judge whether the non-spatial panel model is applicable. LM test results show that the SEM and SAR models are applicable because the test statistics of LM-lag, robust LM-lag, LM-error, and robust LM-error all passed the significance test, indicating that the null hypothesis that SPM or SEM do not exist can be rejected. In the second step, Wald and LR statistics were combined to determine which spatial econometric model to use. The results show that both Wald and LR statistics passed the significance test, indicating that SDM cannot be simplified into SLM and that it is more reasonable to use SDM to fit sample data. The aforementioned test results of the panel econometric model based on the geographical distance spatial weight matrix (W1) are shown in Table 7. The Hausman test rejects the null hypothesis at the 1% level; in order to avoid the influence of unobserved time changes on the estimation results, the spatio-temporal dual-fixed SDM was finally selected for empirical analysis.

TABLE 7 Test results of spatial models.

Test methods	Statistics	Test methods	Statistics
LM-lag test	45.543***	Wald-spatial lag test	198.654***
Robust LM-lag test	43.655***	LR-spatial lag test	89.087***
LM-error test	148.553***	Wald-spatial error test	65.437***
Robust LM-error test	68.643***	LR-spatial error test	79.086***

Note: *** denote significance at confidence level of 1%.

4.1.3 Results of spatial models

Based on different spatial matrices, the regression results for the static and dynamic spatial Durbin models are shown in Table 8. In all four models, ATL has a significantly positive effect on AGTFP, indicating that the estimation model is robust and reliable. In terms of the fitting degree R^2 of the model, the fitting degree of the dynamic spatial Durbin model is higher than that of the static spatial Durbin model, indicating that the dynamic spatial Durbin model is more ideal. This is mainly because the static spatial Durbin model does not consider the dynamic effect of AGTFP in the process of regression,

TABLE 8 Estimation results of spatial Durbin model.

Variable	Static spatial Durbin model		Dynamic spatial Durbin model	
	Model 1 (*W1*)	Model 2 (*W2*)	Model 3 (*W1*)	Model 4 (*W2*)
$AGTFP_{i,t-1}$			0.298***(3.379)	0.243***(3.670)
ATL_{it}	0.358**(3.909)	0.311***(3.487)	0.254***(4.652)	0.223***(4.094)
AIS_{it}	0.203**(3.113)	0.132***(4.191)	0.132***(4.926)	0.287**(3.151)
INC_{it}	−0.144* (-1.969)	−0.075** (−3.103)	−0.123* (-2.158)	−0.111** (-3.125)
TRD_{it}	0.304*** (3.743)	0.273*** (4.211)	0.219** (2.765)	0.186*** (4.176)
DIS_{it}	−0.212* (−2.180)	−0.152* (−2.041)	−0.231** (−3.045)	−0.234** (−3.240)
EDU_{it}	0.114* (2.496)	0.185** (2.989)	0.201* (2.393)	0.132** (2.599)
W^*ATL_{it}	0.171** (3.197)	0.181* (2.153)	0.234** (3.195)	0.179** (3.135)
$Adj\ R^2$	0.811	0.786	0.821	0.781
ρ	0.411*** (3.841)	0.306*** (4.635)	0.225*** (4.819)	0.243*** (5.032)
Log L	142.321	109.043	156.453	142.542

Note: *, **, and *** respectively denote significance at confidence levels of 10%, 5%, and 1% with T values shown in brackets. This table does not report the spatial interaction coefficient of control variables in the SDM mode.

which will also lead to estimation errors. In the regression results of the dynamic spatial panel model, the coefficients of $AGTFP_{i,t-1}$ are positive and pass the significance test of 1%, which fully indicates that AGTFP has a significantly dynamic effect. Agricultural production is a continuous and dynamic economic system, and input and accumulation in its early stage will inevitably be reflected in economic development, technical level, human capital quality, and other factors, which will directly affect the agricultural production activities of this and the following periods.

The dynamic spatial Durbin model based on the geographic distance matrix has the highest degree of fitting, so we mainly analyze the regression results of Model 3 in Table 8. The coefficient of ATL is 0.254 (significant at the confidence level 1%), indicating that agriculture–tourism integration has a positive impact on AGTFP. The integrated development of agriculture and tourism always adheres to the “agriculture-oriented” principle and the ecological development concept, taking agriculture and rural areas as the basic support. The process of integration promotes the intensification, clean production, and management of agriculture, ultimately promoting AGTFP. The coefficient of ATL is significantly lower than that of the static space Durbin model, indicating that this model overestimates the positive effect of ATL on AGTFP. The coefficient of the spatial lag term of ATL (W*ATL) is significantly positive at the 5% confidence level, indicating that there is an interprovincial interaction of ATL and that local ATL will affect the AGTFP of neighboring provinces. It is thus established that ATL has spatial spillover effect on AGTFP.

As far as control variables are concerned, *the agricultural industrial structure* has a significantly positive effect on AGTFP according to Table 8. At the same time, agricultural production has ecological and economic benefits. Increasing the proportion of the planting industry not only improves the agricultural ecological environment but also effectively increases agricultural output value, thus improving AGTFP. *Income distribution* has a significantly negative impact on AGTFP. The greater the income gap between urban and rural residents, the more obvious the priority of industrial and service development is, while agricultural development lags behind. Moreover, the widening income distribution gap will also prompt agricultural producers to focus on increasing income, leading to the excessive use of chemical elements and the increase of pollution emissions. *Trade dependence* has a significantly positive impact on AGTFP. The higher the trade dependence, the higher the degree of the region’s participation in international economic cooperation will be, which not only helps agricultural producers absorb and apply international advanced production technology—increasing the competitive advantage of agricultural products and agricultural producers’ profits—but also reduces pollution emissions. *Disaster-affected degree* has a significantly negative impact on AGTFP. The expansion of the disaster area will not only cause the loss of agricultural output and farmers’ income but also damage the agricultural production environment. *The educational level of the labor force* has a significantly positive impact on AGTFP. The improvement of average education levels not only strengthens the environmental awareness of agricultural producers and improves their production skills but also promotes the optimization of the input factor utilization efficiency of producers, thus improving AGTFP.

Due to the spatial spillover effect, the coefficient of ATL can no longer be interpreted as the marginal effect on AGTFP alone. Therefore, the estimated results need to be decomposed to better reveal the direct (local) and indirect (spatial spillover) effects of ATL on AGTFP. The decomposition results of spatial effects are shown in Table 9. The direct (local) effect of ATL on AGTFP is 0.182 (significant at the 5% confidence level), which indicates that the growth of ATL in a region can cause its AGTFP to increase by

TABLE 9 Decomposition results of spatial effects.

Variable	ATL_{it}	AIS_{it}	INC_{it}	TRD_{it}	DIS_{it}	EDU_{it}
Direct effect	0.182** (3.043)	0.116*** (3.316)	−0.101** (−2.639)	0.194** (3.242)	−0.299** (−2.916)	0.172** (2.684)
Indirect effect	0.130* (2.143)	0.105*** (4.027)	−0.026** (−2.734)	0.095* (2.293)	−0.040 (−0.021)	0.071* (2.459)
Total effect	0.312* (2.283)	0.221*** (3.982)	−0.137* (−1.999)	0.289* (2.235)	−0.339** (−3.164)	0.243** (2.961)

Note: *, **, and *** respectively denote significance at confidence levels of 10%, 5%, and 1% with T values shown in brackets.

TABLE 10 Estimated results of different regions.

Variable	Eastern region	Central region	Western region	Northeast region
$AGTFP_{i,t-1}$	0.385*** (4.279)	0.376*** (3.770)	0.343*** (4.379)	0.365*** (4.760)
ATL_{it}	0.276** (2.578)	0.314** (3.213)	0.191** (3.174)	0.166** (2.665)
AIT_{it}	0.155* (2.113)	0.145* (1.995)	0.129* (2.411)	0.137* (1.997)
INC_{it}	−0.114* (−1.985)	−0.154* (−2.011)	−0.143* (−2.341)	−0.151* (−2.168)
TRD_{it}	0.281** (3.241)	0.276** (3.186)	0.164 (1.663)	0.149* (2.086)
DIS_{it}	−0.232* (−2.132)	−0.265** (−3.211)	−0.309** (−3.042)	−0.215** (−3.121)
EDU_{it}	0.302* (2.215)	0.265** (3.164)	0.209 (1.223)	0.246** (3.214)
$W{*}ATL_{it}$	0.272* (2.332)	0.155** (2.575)	0.149** (2.791)	0.093 (1.175)
$Adj\ R^2$	0.8911	0.8432	0.8224	0.7857
ρ	0.214** (2.841)	0.243** (2.601)	0.197** (2.645)	0.146** (2.635)
$Log\ L$	115.632	143.721	119.654	74.054

Note: *, **, and *** respectively denote significance at confidence levels of 10%, 5%, and 1% with T values shown in brackets.

0.182%. The indirect (spillover) effect of ATL on AGTFP is 0.130 (significant at the 10% confidence level), indicating that a 1% increase of ATL in a region can contribute to a 1.30% increase of AGTFP in its neighboring regions. With the further development and improvement of agro-tourism infrastructure, regions that are the first to overcome the difficulties due to the implementation of a differentiated management mode will be favored by consumers, attracting more consumers from their own and neighboring regions in the short term (Zhang and Gu, 2013). On the other hand, under the pressure of competition, neighboring regions will also make use of local tourism resources to create unique business models. Therefore, the integrated development of agriculture and tourism in a region not only directly drives the development of agro-tourism in a region but also drives neighboring regions to catch up and innovate. The integrated development of agriculture and tourism leads to the upgrading of agricultural infrastructure and the transformation of economic development in a region, thus leading to changes in labor distribution, agricultural industry layout, capital element flow, and modes of land transfer in neighboring areas, and improving the quality of ecological environment protection and agricultural development in neighboring areas, which is beneficial for the improvement of their AGTFP. It should be noted that, although indirect effects pass the significance test, their significance level is 5%, which is lower than the 1% significance of direct effects. The possible reason for this is that the fierce homogeneous competition in China's agro-tourism market is relatively serious, coupled with the interference of consumers' aesthetic fatigue, difficulty in choosing, and psychological gap, so that the spatial spillover effect of ago-tourism integration is limited.

4.1.4 Results of regional heterogeneity analysis

In view of the great differences in tourism and agricultural development among different regions in China, this study divided the whole research region into east, middle, west, and northeast for empirical testing. The model estimation adopted the dual-ways fixed SDM model based on the geographical distance spatial weight matrix, with results in Table 10. As can be seen from the analysis results, the estimation results of the four regions are basically consistent with the whole region's samples: the direct (local) effect and the spatial spillover effect are both significant. This shows that the aforementioned research results are relatively robust. The coefficients of $AGTFP_{i,t-1}$ all passed the significance test, indicating that all regional AGTFP was affected by the efficiency of the previous stage. All the four regional spatial autocorrelation coefficients ρ are greater than 0 and pass the significance test, which indicates the existence of the spatial

TABLE 11 Decomposition results of spatial effect in different regions.

Variable	Eastern region	Central region	Western region	Northeast region
Direct effect	0.251** (3.195)	0.312** (2.947)	0.137** (3.191)	0.123** (3.131)
Indirect effect	0.131** (2.931)	0.099** (3.125)	0.076** (2.626)	0.045 (1.005)
Total effect	0.382** (2.814)	0.411** (3.163)	0.203** (2.853)	0.168** (1.982)

Note: ** denotes significance at confidence level of 5%.

TABLE 12 Threshold effect test.

Threshold variable	Model test	Threshold estimate	F statistic	*p*-value	Critical values		
					1%	5%	10%
ATL	Single threshold	0.603	28.117***	0.001	26.097	15.654	9.813
	Double threshold	Threshold 1:0.603	0.098	0.298	13.911	7.987	4.874
		Threshold 2:0.702					
	Triple threshold	0.581	2.432	0.198	8.987	6.686	4.116

Note: *** denotes significance at confidence levels of 1%.

spillover effect of AGTFP. In addition, the coefficients of W^*ATL_{it} in the eastern, central, and western regions are significantly positive, indicating that the ATL of a local region can have a positive spatial spillover effect on the AGTFP of its neighboring regions, although this effect is not significant in the northeast region.

At the same time, the direct (local) effect and spatial spillover effect of ATL on AGTFP are considered the difference of the spillover effect in different regions. The results of spatial effect decomposition are shown in Table 11. In terms of direct (local) effect, the central region has the strongest direct (local) effect (coefficient = 0.312, significant at 5% confidence level). The spillover effect of ATL on improving AGTFP in eastern region (the = 0.131, significant at 5% confidence level) is greater than those of other regions. Comparatively speaking, the eastern region has a good economic foundation and infrastructure, so tourism, information, and factor flows can operate conveniently and efficiently. Therefore, the spillover effect in the eastern region is more prominent.

4.2 Results of dynamic threshold regression model and analysis

First, the threshold value and number of threshold variables should be determined. The threshold value of ATL obtained by 300-times self-sampling using the Bootstrap method is shown in Table 12. The results show that the F statistic of a single threshold of ATL passes the test at a 5% significance level, with a threshold value of 0.603. Because neither double nor triple thresholds pass the significance test, a single threshold panel threshold regression model for empirical testing was thus established.

Biased results will be obtained if the OLS method used to estimate the threshold regression model contains lagged items of explained variables. Therefore, the system generalized method of moments (GMM) method is used here for estimation, with regression results shown in Table 13. When ATL (of the whole research region) is lower than the threshold value of 0.603, its regression coefficient is 0.207 (significant at 5% confidence level), which passes the test at 5% significance level. When ATL exceeds 0.603, the regression coefficient is 0.394 (significant at 5% confidence level). This indicates that, with increased agricultural–tourism integration, its effect on AGTFP is generally enhanced.

At the same time, the dynamic panel threshold effects were estimated for four different regions, and the number of threshold values and variables in different regions were determined. It was found that there was just one threshold value in each of the four regions (Table 13). As shown in Table 13, the eastern region has the lowest threshold value (ATL = 0.573) of the four regions. When ATL is less than the threshold value, its regression coefficient is 0.221 (significant at 1% confidence level), and, when ATL crosses the threshold value, its coefficient increases to 0.416 (significant at 1% confidence level). The eastern region has convenient transportation, suitable climate, and a higher urbanization and economic level, so its residents have a higher demand for agro-tourism. With improved integration of agriculture and tourism, the agricultural ecological value is further highlighted, which also enhances of the ecological consciousness of agricultural producers. They will therefore take the initiative to adopt green production methods and strengthen agricultural ecological and environmental behavior to enhance AGTFP. The western region has the highest threshold value (ATL = 0.621). When ATL is less than the threshold value, its influence coefficient is not significant, but when it crosses the threshold value, its coefficient increases to 0.289 (significant at

TABLE 13 Threshold effect estimation results.

Region	Explanatory variable	Threshold estimate	Coefficient	T value	Standard error
Whole region	ATL	ATL≤0.603	0.207**	3.035	0.001
		ATL>0.603	0.394**	2.986	0.025
Eastern region	ATL	ATL≤0.573	0.221***	5.098	0.007
		ATL>0.573	0.416***	3.805	0.087
Central region	ATL	ATL≤0.581	0.298***	4.981	0.002
		ATL>0.581	0.411***	3.912	0.011
Western region	ATL	ATL≤0.621	0.177	1.093	0.132
		ATL>0.621	0.289**	2.775	0.014
Northeast region	ATL	ATL≤0.594	0.172*	2.313	0.072
		ATL>0.594	0.207**	3.211	0.032

Note: *, **, and *** denote significance at confidence levels of 10%, 5%, and 1%, respectively.

5% confidence level). This indicates that, when the level of agricultural–tourism integration in western China is relatively low, it cannot significantly promote the growth of AGTFP; only when ATL climbs to a higher level is its impact on improving AFTGP significant. This is mainly because most western provinces are economically underdeveloped, so it is difficult to promote advanced agricultural technology, and the market space of agricultural tourism is relatively limited. In addition, natural resources and climate conditions in this region are poor, so it is more difficult to promote agriculture–tourism integration. Therefore, ATL has no significant influence on AGTFP in the early stage of integration. When ATL exceeds the threshold of 0.621, agro-ecological capital can create more value for agricultural producers, leading them to pay more attention to agricultural green development. They will then consciously reduce the input of harmful environmental elements in the production process, ultimately improving AGTFP and enhancing the effect of ATL on AGTFP.

5 Conclusion and policy recommendation

5.1 Conclusion

Based on the panel data of 30 provinces in China from 2008 to 2019, this study used the dynamic spatial Durbin model and threshold model to verify whether the integration of agriculture and tourism can promote AGTFP. The conclusions of this study are

(1) During the study period, AGTFP in the whole study area showed an upward trend, though there were fluctuations, and the average annual growth rate was 2.26%. The average annual growth rates of AGTFP in the eastern, central, western, and northeastern regions during the study period were 2.06%, 2.31%, 2.53%, and 2.10%, respectively. In recent years, the central government has attached great importance to environmental protection, aimed at agricultural pollution, which has greatly contributed to the growth of AGTFP.

(2) The impact of agriculture–tourism integration on AGTFP has a spatial spillover effect. The improvement of this integration in adjacent areas is conducive to increased AGTFP in the local region. For the whole research region, the direct (local) effect of ATL on AGTFP is 0.181, indicating that the growth of ATL in a region can lead a region's AGTFP to increase by 0.181%. The spillover effect of ATL on AGTFP is 0.130, indicating that a 1% increase of a region's ATL contributes to a 1.30% increase of AGTFP in its neighboring region. As for different regions, the central region has the strongest direct (local) effect, while the spillover effect of ATL on AGTFP in the eastern region is the greatest of the four regions.

(3) There is a threshold effect of agriculture–tourism integration on AGTFP, and there is a single threshold in the whole area and four different subdivisions. When the ATL of the whole research region is lower than the threshold value of 0.603, the regression coefficient of ATL is 0.207; however, when ATL exceeds 0.603, the regression coefficient increases to 0.394. This indicates that, with the increase in ATL, its effect on AGTFP is enhanced. Among the four regions, the eastern region has the lowest threshold value (ATL = 0.573), while the threshold value of ATL in the western region is the highest (ATL = 0.621). When the ATL of the western region is below the threshold value, its effect on AGTFP does not pass the significance test; only when it exceeds the threshold value does it have a significantly positive effect on AGTFP. Therefore, improving ATL is important for promoting AGTFP.

5.2 Policy recommendation

The conclusions of this study provide the following recommendations for promoting agriculture–tourism integration and giving full play to its role in improving AGTFP:

(1) Top-level design of policies and institutions should be optimized and improved. Incorporating the integrated development of agriculture and tourism into the framework of agricultural green development should be taken into consideration. All regions should fully combine the characteristics of resource endowment and systematically plan and jointly develop agricultural and tourism resources and elements. It is very important to promote the effective integration of the industrial and value chains of agriculture and tourism and to promote the deeply integrated development of the two industries. It is also necessary to build an integrated agglomeration area of agriculture and tourism to achieve industrial agglomeration.
(2) Considering the positive spatial spillover effect of the integration of agriculture and tourism, the timely promotion of regional coordination mechanisms by exploring a reasonable development model for dividing economic zones and administrative regions is necessary. Practical regional cooperation should be strengthened by signing strategic cooperation agreements and promoting effective cooperation between administrative regions in many ways, such as platform construction, industrial integration, public services, and personnel exchanges. Difficulties such as the consolidation of interests, homogenization of competition, lagging administrative control, and lagging institutions in trans-regional governance should be resolved effectively.
(3) We should find ways to innovate the development of agriculture–tourism integration, thus promoting the upgrading of the agro-tourism association. Promoting the knowledge, management, and technology of agriculture–tourism integration spills over into relevant agricultural operating subjects. We can thus optimize the allocation of agricultural labor, land, capital, technology, management, and other production factors to improve the overall agricultural technological progress and efficiency, thus also improving AGTFP.
(4) Rural human capital cultivation should be strengthened. Promoting the integrated development of agriculture and tourism requires the support of high-quality skills. Developing agro-tourism requires flexible measures and recruiting talent, basic skilled personnel, middle or senior management, and operations personnel. At the same time, rural vocational and technical education should be strengthened, agricultural technology should be promoted, and the vocational skills of local laborers should be improved to enhance the level of rural human capital, which will better help agricultural–tourism integration promote AGTFP.

Although this study has determined the spatial and non-linear effects of agriculture and tourism integration on AGTFP, it has some limitations. First, we only conducted a theoretical analysis of the influence mechanism of the integration of agriculture and tourism on AGTFP, which should be further empirically tested. Second, the study period in this paper ends in 2019. Considering the huge impact of COVID-19 on tourism since 2020, official statistical data from 2020 and later were not included in the research observation period of this paper. In the future, statistical data should be continuously tracked and updated, especially focusing on the integrated development and evolution of agriculture and tourism after the start of the 14th Five-Year Plan of China. Third, due to data limitations, we conducted the empirical research at the provincial level; in future, more micro-analysis will be carried out by selecting typical cases, such as national demonstration counties of leisure agriculture and rural tourism or key villages of rural tourism, so as to improve the accuracy of the research conclusions.

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 wrote the manuscript, and FZ contributed to manuscript revision, read, and approved the submitted version. CC revised the format of the manuscript, and ZL polished the language and corrected grammatical errors.

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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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Material balance principle to estimate eco-efficiency of saffron-producers aiming reduction in greenhouse gas emissions in Iran

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Introduction: During the last decades, environmental pollution has been considered one of the challenges of the agricultural sector, which has affected the relationship between the ecological and economic performance of agricultural products.

Methods: In this study, the DEA-MBP approach based on the SBM model has been used to investigate the eco-efficiency of saffron farms in Iran. The main purpose of this approach is to decrease GHG emissions by mitigating the use of highly polluting production inputs.

Results: The results showed that the average eco-efficiency is estimated at 74% and is 12% lower than technical efficiency without considering environmental issues. Therefore, saffron producers are 26% far from full efficiency, and they must change their consumption of inputs and production of inputs according to environmental issues in order to achieve it. Excessive use of diesel fuel and fungicides is cause of GHG emissions in these farms.

Discussion: The use of sustainable and ecological cultivation methods in farms in order to reduce the consumption of chemical fertilizers and fungicides should be considered. Replacing old machinery and repairing them can also considerably reduce fuel consumption and GHG emissions.

KEYWORDS

data envelopment analysis, undesirable output, chemical fertilizer, excess carbon dioxide, Ghayenat County

1 Introduction

One of the important and complex problems in agriculture is considering the mutual relationship between economic development and the environment. Although agricultural activities are essential to human society and have some advantages such as food supply, income for farmers, and the growth and development of rural areas, these activities have caused the 26% of GHG emissions and climate change at the international level from 2006 to

2016 (FAO (2018). Maintaining environmental quality and balance between human activities to pursue the objectives of economic development and the capacity of natural regenerative resources is one of the global challenges. For this purpose, several international organizations such as the UN and the UNFCCC have pushed for the realization of the sustainable development paradigm. However, the prevalence of unsustainable agriculture in most countries has raised widespread concerns in the international arena. It has turned the need to consider the increasing economic gains given the importance of sustainable development as one of the challenges for researchers and policymakers (Martinsson & Hansson, 2021).

Estimating ecological and economic efficiency (EEE) or eco-efficiency in different sectors of agriculture has received much attention from researchers on how to increase sustainability in agriculture. Eco-efficiency was introduced as an operational concept to assess sustainability in 1990 (Schaltegger, 1996), and it was revised by the World Trade Council for Sustainable Development to encourage producers to compete and be more environmentally friendly in 1992 and 2000 (Schmidheiny, 1992; WBCSD, 2000). In fact, by estimating EEE, it is determined to what extent environmental damage can be reduced and, by minimizing damage to the environment, sustainable development can be improved in economic enterprises (Pang et al., 2016; Güngör et al., 2022).

Eco-efficiency can be used at both macro and micro levels. At the macro level, the concept of EEE reminds us that GDP growth should not be related to negative effects on the environment as much as possible. Besides being satisfied with the increase in consumption of goods, society should benefit from a good quality environment (Zhong et al., 2022). At the micro level, EEE means that greater economic value can be achieved with less environmental damage. It should be mentioned that since this measure is relative, its improvement does not necessarily guarantee the production's sustainability, and to ensure sustainability, definite amounts of pressure imposed on the environment should be considered (Huppes & Ishikawa, 2005). However, despite the limitations of EEE, this measure is very important and popularity. One of the advantages of EEE is the identification of actionable policy goals rather than mandatory activities such as limiting the level of economic activity. Improving EEE includes units that often do not produce at the economic efficiency Frontier; Therefore, in addition to reducing environmental effects, there is an opportunity to save production costs (Ekins, 2005).

Saffron planting is considered a strategic and vital component of the national economy of Iran due to its unique position in job creation in the agricultural sector and the creation of significant foreign exchange income for this country. Some of the particular advantages of saffron are low irrigation, high product durability, exploitation for 5–7 years in one planting period, ease of transportation, productive employment, and significant currency enhancement, which has led to the development of its cultivated area in Iran, especially in areas without agricultural potential (Saeidi et al., 2022). The product's compatibility has made Iran the largest producer of saffron in the world, producing 430 tons of saffron in 2019, more than 90% of global production and 3.5% of global market share (Statista, 2020). Given the benefits of saffron cultivation, increasing the production and yield of this product also has caused many environmental problems. The negative consequences of saffron cultivation have been estimated as GHG emissions and nitrogen and phosphorus flow of 18.54, 8.18, and 5.18 million tons per year, respectively, in Khorasan Razavi province, Iran (Bakhtiari et al., 2015). Thus, considering the environmental pollution in calculating the efficiency of saffron-producing units can identify the units that have been active in economic saffron production and have caused the least damage to the environment, and introduce them as a suitable model for others. In this regard, the present study examined this criterion at the level of saffron farms and identified the inputs that had the most significant impact on eco-inefficiency by determining the factors related to eco-inefficiency.

1.1 Review of literature

To estimate efficiency, there are two main approaches, parametric and non-parametric. Parametric approaches are specified by a functional form, while non-parametric approaches do not require an specific functional form (Mardani Najafabadi et al., 2023). Currently, one of the most widely used methods of evaluating efficiency in agricultural production is data envelopment analysis (DEA), which is known as a non-parametric approach. The main advantage of this method is the ability to use multiple inputs and outputs to measure the relative efficiency of a set of homogeneous decision-making units or DMUs (Sabouhi & Mardani, 2017). On the other hand, one of the topics that have been the focus of researchers in the field of efficiency evaluation with regard to environmental issues is the Material Balance Principle (MBP). The law of conservation of matter/energy is a basic biophysical condition that states that the flow leaving or entering the environment is equal or balanced. However, Lauwers (2009) stated that MBP had been neglected in most studies conducted in this field. One of the most common models in the field of introducing undesirable data into efficiency measurement models is the Directional Distance Functions (DDF) introduced by Chung et al. (1997). However, despite the popularity of this model and many models of EEE estimation, Coelli et al. (2007) raised many criticisms that these models are not compatible with MBP.

Many studies have been conducted in examining EEE and various efficiency indicators have been used for this purpose. The first studies in this field have generally attentive to the effect of pollution control on economic growth at the macro level (Christainsen & Haveman, 1981; Gollop & Roberts, 1983; Färe et al., 1989). Using this method, several limited studies have been performed at the micro level, including the study of Pashigian (1984) and Pittman (1981). Later, Pittman (1983) calculated the EEE of Wisconsin paper factories by incorporating environmental variables into common productivity indicators. In this method, pollution is considered a cost variable. The important point about adjusted productivity indicators is that, unlike conventional inputs and outputs (IOs), the price of undesirable variables such as pollution is not known, and some proxies (observed indicators such as pollution taxes) should be used for the price of these variables (Coelli et al., 2007). The first studies that included environmental variables were also evaluated on the assumption that reducing pollution is a costly activity.

In general, environmental efficiency studies can be classified into two important categories by considering environmental pressure variables as undesirable inputs or outputs (Long, 2021). A large part of the first studies in this field have incorporated environmental pressures such as pollution or waste increase as undesirable inputs or outputs into efficiency measurement models (Tyteca, 1997), and the other part focused on the explanation of EEE as the economic value ratio and environmental damage (Kuosmanen & Kortelainen, 2005), much attention was paid to ecological characteristics, and unlike the first category models in which physical IOs entered the model directly, only economic value added and environmental variables were included in the model (Kuosmanen & Kortelainen, 2005; Picazo-Tadeo et al., 2011; Martinsson & Hansson, 2021).

Many studies in the first category have used Frontier models to measure the EEE introduced by Tyteca (1997). These models are placed in two categories of parametric and nonparametric Frontier approaches. Lauwers (2009) in his study showed that most studies on efficiency measurement models, including nonparametric Frontier models, have not considered the MBP. Coelli et al. (2007) also examined some studies in EEE with DEA models (Färe et al., 1989; Färe et al., 1996; Reinhard et al., 2000) and showed that these studies are only compatible with MBP requirements in certain conditions and do not comply with this principle in general. In this regard, Coelli et al. (2007) criticized the DEA models used in these papers, including the DDF model that is matchable with MBP requirements. In another study, the network DDF model combined with the MBP was used to estimate the EEE of coal-fired power plants in the US (Färe et al., 2013).

Among the drawbacks of the DEA-MBP model presented by Coelli et al. (2007) model is that, first, it does not consider the actual amount of pollution that is difficult to find in agriculture. Also, this model cannot show the difficulty of the production and disposal of pollutants. Finally, when the number of inputs is too large, the validity of the results is severely influenced (Arabi et al., 2017). Overall, a more inclusive and MBP-compliant model is needed to measure EEE. Later, Arabi et al. (2017) provided a complete model, including input-orientation and easy application of others, and the inability of distance models and Slacks-Based models (SBM) introduced by Färe et al. (2013) in determining the optimal composition of fuels.

According to review studies done by Zhou et al. (2018) and Emrouznejad and Yang (2018), the agriculture sector had the highest focus of studies during 2015–2016. Many studies have also applied the DEA approach in this area, including Grassauer et al. (2021) who used a combination of DEA and LCA approaches to estimate the EEE of Austrian farmers with different types of agricultural activities.

Martinsson and Hansson (2021) examined the EEE of the dairy farmers in Austria and used zero net emissions by 2045 to determine a specific emissions threshold. Some research shows that most industrialized countries such as China have low EEF (Yao et al. (2018); Pang et al. (2016) examined the EEE of the agricultural sector in China. For this purpose, he used the DEA technique and the Theil index. In this study, non-radial SBM models have been used, and several undesirable outputs of total nitrogen, total phosphorus and agricultural plastic waste have been considered; Gómez-Limón et al. (2012) calculated the EEE of olive farms using the DDF and distinguished in Andalusia (Spain). Picazo-Tadeo et al. (2011) examined the EEE of drip-irrigation farms in Castilla y León (Spain). The study of several environmental indicators and the calculation of deficiency and excess of these indicators for production units were among the innovations of his study.

Selecting environmental-economic variables based on type of activity is one of the important issues in the study of EEE. In some studies, various variables have been used as environmental pressure indicators. Nemecek et al. (2011) divided environmental indicators into three main groups: resource, nutrient, and pollution indicators. Each category considers different aspects of the environment and different management options. For example, Martinsson and Hansson (2021) considered the cost of fuel, heating equipment, and the cost of fertilizers as indicators of environmental pressure. Grassauer et al. (2021) used cumulative energy demand, normalized eutrophication potential, and global warming potential. Urdiales et al. (2016) used carbon dioxide emission data. Arabi et al. (2017) applied sulfate gas produced in a power plant over a 1-year period as an indicator. Mulwa et al. (2012) selected excess nitrogen and phosphate fertilizers as the environmental pressure indicators.

After thorough research on different past studies and environmental data, we applied excess carbon dioxide equivalent as an environmental pressure indicator in the present study. It is worth mentioning that no study has been done so far to calculate the EEE of saffron, and only in some, environmental issues of cultivation of this crop have been investigated. For example, in the study of Bakhtiari et al. (2015), the emission rate equivalent to carbon dioxide in the saffron production cycle during 5 years was calculated using conversion coefficients of inputs. Feizi et al. (2015) investigated the energy efficiency of saffron in Khorasan Razavi province. According to their study, saffron farms had an stable and efficient system (economically) in the Khorasan Razavi province.

Thus, this study aimed to investigate the EEE of saffron producers using the DEA-MBP model. In addition, examining the difference between the optimal consumption of inputs in the two cases, with and without considering the environmental pressure is another goal. In general, this study has contributed to the literature in two aspects. First, the DEA-MBP method has not been used in agriculture so far. Second, the calculating method of the environmental pollutant variable has been introduced for the first time; thus, the interaction of the environmental and economic variables is better indicated. In addition, this type of calculation is consistent with the limitations of the lack of proportionate GHG emission data from agricultural activities and provides valuable information to the researcher.

1.2 Case study

Saffron is widely cultivated in Iran due to its high added value. The main centers of saffron production in this country are the Khorasan Razavi and South Khorasan provinces and 76% of Iranian saffron is produced in these two provinces (Statista, 2020). South Khorasan province ranks second in saffron cultivation with 17,000 ha of cultivated area and production of 66 tons of this product. Meanwhile, Ghaen County is considered the saffron capital of Iran and with an global brand in saffron production in terms of the quality of this product (Bazrafshan et al., 2019). This County is located in the east of Iran and the north of South Khorasan province at latitude: 15.33 and longitude: 34 and 38.58–56.60 (Figure 1). The climate of this County is highly influenced by the

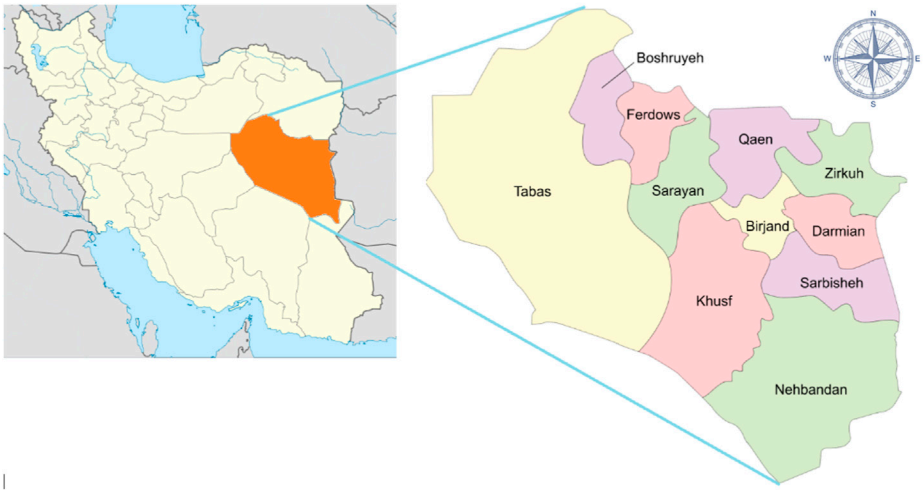

FIGURE 1
Geographical location of Ghaen County.

heights of the mountains are stretched in the vicinity of that. Ghaen County is located such that at the beginning of the cold season, it is announced as the coldest point in Iran (Khanali et al., 2017). The average annual rainfall in this County is 180 mm, and it is recognized as the rainiest County in the province. The fluctuations and changes in temperature are high in Qaen both temporally and spatially. The range of average monthly temperature changes during the year is 23.5°C. The absolute maximum and minimum are 41oC and 28°C, respectively. Due to the geographical and climatic location of this County, the cultivation capability of strategic crops such as saffron is of great importance (Statistical Center of Iran, 2020).

2 Materials and methods

In this study, to calculate the EEE at the farm level, the DEA-MBP model developed by Arabi et al. (2017) was selected and adjusted based on the IOs of saffron production and the appropriate environmental pressure index. In this section, first, the DEA model and the MBP were explained, and the integration of MBP requirements in DEA models was also discussed. Then, a comprehensive model of EEE, considering the inputs in three categories of high and low pollutants and independent variables are presented. Finally, the IOs used in the research and how to estimate them are explained. The conceptual framework of the steps to determine the EEE of saffron is shown in Figure 2. The following presents the additional explanations of this Figure.

2.1 Data envelopment analysis (DEA)

DEA is a non-parametric method that determine the efficiency of those DMUs that have similar IOs using the linear programming and does consider the basic assumption of a consequential relationship between IOs (Mardani Najafabadi & Taki, 2020). As this approach encompasses all numbers and information, it is known as comprehensive data analysis. This method is used in the study of Charnes et al. (1978) based on Farrell's approach. Then, efficiency calculations in different conditions were invented and introduced by different DEA models (Emrouznejad & Yang, 2018).

2.1.1 The conditions of DEA-MBP models

In the following, first the conditions of material balance and incompatibility of DDF model with these conditions are expressed. To use MBP Equations, if α and b are defined as the non-negative coefficients, the amount of pollution can be calculated as:

$$Z = \alpha' X - b' y \tag{1}$$

Where X, y and Z are inputs, outputs and pollution rate per unit of production, respectively.

The DDF model is that the model seeks the maximum amount of θ that can keep the vector X, $y + \theta y$, and $Z - \theta Z$ within production possibility set. If these vectors are substituted in Eq. 1, we obtain: $Z - \theta Z = \alpha' X - b'(y + \theta y)$.

For efficient units, if = 0 , the unit is located on the Frontier and the MBP is established.

The Coelli et al. (2007) model can be represented as model (2) by considering N DMUs:

$$\begin{aligned} &\sum_{n=1}^{N} \lambda_n X_{ni} \le X^e_{oi} \;\; i = 1, \ldots, I \\ &\sum_{n=1}^{N} \lambda_n y_{nj} \le y_{oj} \;\; j = 1, \ldots, J \\ &\lambda_n \ge 0, \;\; n = 1, \ldots, N \end{aligned} \tag{2}$$

where o represents the DMU under study, X^e_{oi} is calculated to find the best input to produce the lowest amount of pollution, X_{ni} and y_{nj} represent the ith input and jth output of n unit, respectively, and λ_n is the unit vector of fixed values. Despite This DEA-MBP model benefits, as mentioned earlier, some of its limitations cause inadequacy in application for some industries.

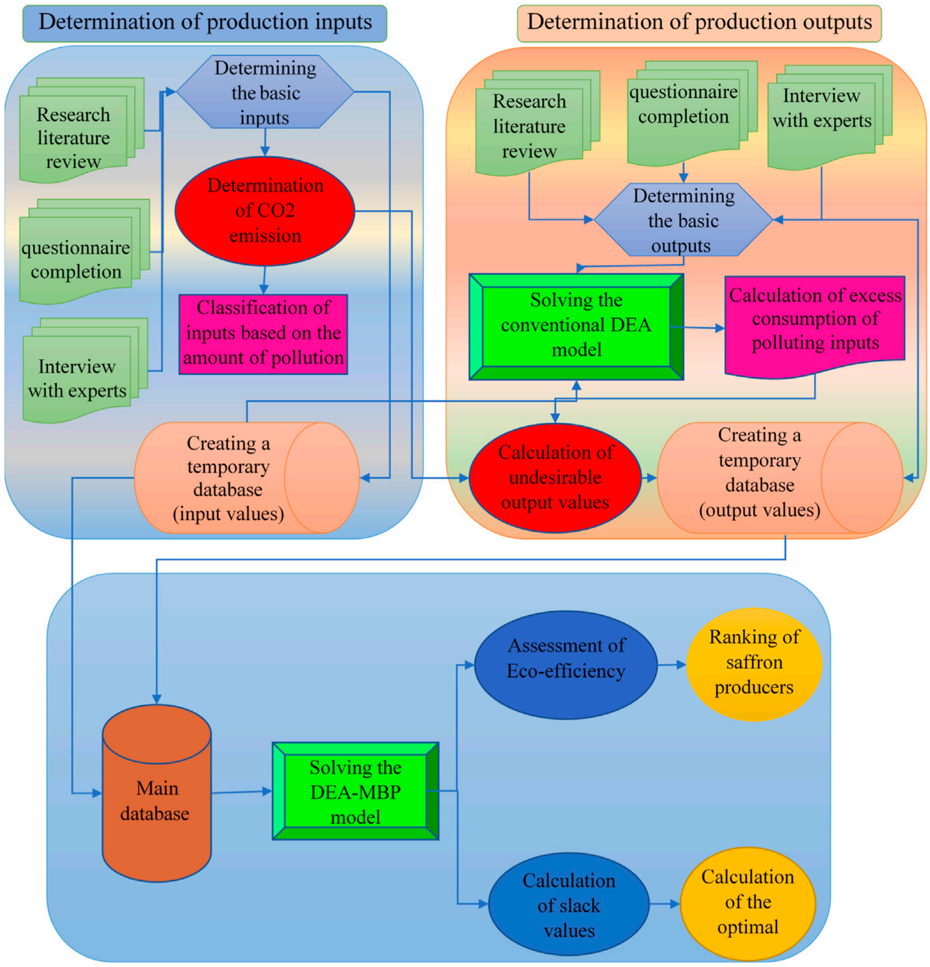

FIGURE 2
Conceptual framework to determine the EEE of saffron.

2.1.2 Modified DEA-MBP model

There are several models that comply with the MBP requirements. Here is an SBM model for calculating inefficiency as model (3) (Färe & Grosskopf, 2010):

$$
\begin{aligned}
&D_o(x, y) = Max \sum_{i=1}^{I} a_i + \sum_{j=1}^{J} \beta_j \\
&S.t. \\
&\sum_{n=1}^{N} \lambda_n X_{ni} \le X_{io} - a_i.1; \quad i = 1, \ldots, I \\
&\sum_{n=1}^{N} \lambda_n y_{jn} \ge y_{jo} + \beta_j.1\,; \quad j = 1, \ldots, J \\
&\lambda_n \ge 0, \beta_j \ge 0, a_i \ge 0; \quad i = 1, \ldots, I, j = 1, \ldots, J, n = 1, \ldots, N
\end{aligned}
\tag{3}
$$

Finally, in order to model EEE in a wider way and to solve the defects of model 3, the inputs are classified into two categories of high and low pollutants. Based on this, the EEE model is presented as an alternative to model (4):

$$
\begin{aligned}
&D_o(X, y, Z) = Max \sum_{l=1}^{L} al_L + \sum_{h=1}^{H} ah_h + \sum_{m=1}^{M} a_m + \sum_{j=1}^{J} \beta_j + \sum_{k=1}^{K} \gamma_k \\
&S.t. \\
&\sum_{n=1}^{N} \lambda_n xl_{ln} \le xl_{lo} + al_l \cdot 1;\ l = 1, \ldots, L \\
&\sum_{n=1}^{N} \lambda_n xh_{hn} \le xh_{ho} - ah_h \cdot 1;\ h = 1, \ldots, H \\
&\sum_{n=1}^{N} \lambda_n x_n \le x_{mo} - a_m \cdot 1\,;\ m = 1, \ldots, M \\
&\sum_{n=1}^{N} \lambda_n y_{jn} \ge y_{jo} + \beta_j \cdot 1\,;\ j = 1, \ldots, J \\
&\sum_{n=1}^{N} \lambda_n z_{kn} = z_{ko} - \gamma_k \cdot 1\,;\ k = 1, \ldots, K \\
&\gamma_k - \sum_{j=1}^{J} b_{jk}\beta_j = \sum_{h=1}^{H} ah_{hk} ah_h - \sum_{l=1}^{L} al_{lk} al_l;\ k = 1, 2, \ldots, K \\
&\lambda_n \ge 0, al_l \ge 0, ah_h \ge 0, \gamma_k \ge 0, a_m \ge 0, \beta_j \ge 0;\ n = 1, \ldots, N, i = 1, \ldots, I, \\
&k = 1, \ldots, K, m = 1, \ldots, M, h = 1, \ldots, H, l = 1, \ldots, L, j = 1, \ldots, J
\end{aligned}
\tag{4}
$$

The definition of symbols in this model is as follows:

xh: high pollution inputs
xl: low pollution inputs
x: non-polluting inputs
αh: rates of reduction and expansion of high emissions
αl: rates of reduction and expansion of low emissions
α: rate of reduction of non-polluting inputs
ah: The share of inputs pollution with high pollution
al: The share of inputs pollution with low pollution

Obviously, we should have $\alpha h > al$, because if have $\alpha h = al$, there is no need to distinguish between high and low pollution. Thus, as one of the requirements of mathematical programming models, $H + L + M = I$ should be here, where I indicates the total number of inputs.

2.2 Statistical sampling

The statistical population of this research is saffron producers in Ghaen County in South Khorasan province in Iran. The data used for the DEA-MBP model (Eq. 4) is cross-sectional. Therefore, the information needed to calculate the EEE was collected by completing 237 questionnaires by saffron growers in the region in 2020 using random sampling.

2.3 Input and output (IO) data

The input and output data used in Model (4) are explained below. In past studies in the field of investigating the efficiency of saffron farms, these variables have been used as the main inputs and outputs (Bakhtiari et al., 2015; Feizi et al., 2015). In this model, the inputs used were classified into three groups of inputs with high pollution, low pollution, and independent variables. Thus, to achieve greater EEE, we can replace low-emission inputs with high-emission inputs. Also, the environmental pressure variable enters the model as an undesirable output, to increase the desired output (economic variable) and minimize environmental pollution. In the present study, the equivalent carbon dioxide excess is considered as a variable of environmental pressure (Nemecek et al., 2011; Picazo-Tadeo et al., 2011; Urdiales et al., 2016; Grassauer et al., 2021; Martinsson & Hansson, 2021). In order to calculate this variable, the conventional DEA model was first estimated and the input consumption excess was calculated. Finally, using the GHG conversion coefficients, the CO_2 equivalent of pollutant inputs was calculated and its sum as the undesirable output entered the model (Figure 2). Also, based on the EEE model, the inputs used were divided into three categories of inputs with high pollution, low pollution and independent variables. The classification of these inputs was performed according to the conversion coefficients of GHG. Thus, the inputs with a conversion coefficient higher than 1, was assigned to highly-pollutant inputs and inputs with a coefficient of less than 1 were dedicated to the low-pollutant inputs (Guo et al., 2022). Also, two inputs of water and seed are independent inputs in this study.

2.3.1 Production inputs

1- **Seed**: Saffron cormis the main factor in the growth of saffron flowers and choosing a good daughter corms from mother corms is one of the most significant factors affecting the quality of saffron. This corm is usually oval-shaped and contains brown straws that protect it from dryness and soil heat by absorbing moisture.
2- **Water**: Suitable water supply in terms of quantity, quality and irrigation schedule is a key strategy in achieving appropriate saffron yield. Saffron has high irrigation efficiency and drought tolerance, and although it needs irrigation in arid regions such as Iran, it has less irrigation requirement than other conventional agricultural products. Experts believe that plants that have more main root length, number of lateral roots, root length density and root-to-shoot ratio are more resistant to drought tolerance (Farooq et al., 2009).
3- **Chemical fertilizers**: Phosphate, nitrogen, and phosphorus fertilizers are the most widely used chemical fertilizers in saffron cultivation. The determination of the amount of use of these fertilizers, according to the amount of these elements in the farm soil and also their timely use, in addition to affecting the amount and quality of saffron, it is effective on the amount of GHG emissions and pollution of water resources.
4- **Animal manure**: Animal manure is used to provide the organic matter needed by the saffron plant. The replacement rate of this fertilizer with chemical fertilizers and determining the appropriate time of its use affects the quality and quantity of saffron products.
5- **Fungicides**: The color, smell and taste of saffron are attractive to many rodents, birds, insects, etc. One of the methods to fight against pests and diseases of saffron is to disinfect the bulbs with fungicides and acaricides before planting. Also, the fungicides are useful to prevent or minimize the attacks of fungi as Fusarium oxysporum and Rhizoctonia violacea.
6- **Manpower**: This variable is the number of hours of manpower use per hectare during the production period of saffron. In Iran, for saffron cultivation, high manpower is used compared to conventional crops such as wheat. However, according to some studies, the number of manpower decreases with increasing land size, which indicates an increase in dependence on machinery with increasing land size.
7- **Machinery**: In different stages of planting, growing and harvesting saffron products, different machines are used along with manpower and as a substitute for manpower. The total hours of use of these machines per hectare has been used as a machineries variable in estimating the efficiency of saffron.
8- **Diesel fuel:** The use of agricultural machinery from fossil fuels is one of the main causes of GHG emissions. The amount of diesel fuel used per hectare has been used as one of the input variables in calculating efficiency. The use of old and disproportionate machines with agricultural operations and farm area is one of the factors of high fuel consumption in saffron fields.

2.3.2 Production outputs

As mentioned before, in this study, saffron stigma is considered as a desirable output and the equivalent carbon dioxide excess GHG as an undesirable output.

1- **Saffron stigma**: Saffron stigma is the most important part of saffron that is used as coloring and flavoring agent. Therefore, the

TABLE 1 GHG conversion coefficients of saffron production inputs.

Inputs	Unit	Equivalent to kg of CO2 per unit	Sources
Potassium	kg	0.15	Lal (2004)
Nitrogen	kg	1.3	Lal (2004)
Phosphate	kg	0.2	Lal (2004)
Manure	Ton	0.005	Mohammadi et al. (2014)
Fungicides	kg	3.9	Lal (2004)
Machinery	MJ	0.071	Khoshnevisan, Rafiei, et al. (2013a)
Fuel	Liter	2.76	Khoshnevisan, Rafiei, et al. (2013b)
Electricity	kWh	0.608	Khoshnevisan, Rafiei, et al. (2013a)
Manpower	hour	0.7	Nguyen & Hermansen (2012)

TABLE 2 Statistical description of IOs used in saffron cultivation in Ghaen County per hectare.

			Unit	Average	Minimum	Maximum	Coefficient of variation
Inputs	Low-Polluting	Potassium	kg	5.67	0	96	277.96
		Phosphate	kg	11.17	0	250	275.70
		Manure	Ton	32.19	10	90	53.20
		Manpower	hour	972.56	227	3,024	45.59
		Electricity	kWh	22,383.01	8,384	39,300	18.38
	High-Polluting	Nitrogen	kg	62.37	0	350	79.87
		Fungicides	kg	1.72	0	3	48.80
		Machinery	MJ	41.96	8.67	93.33	39.04
		Fuel	Liter	535.16	94	1,535	42.37
	Independent	Seed	kg	5,682.74	500	50,000	78.51
		Water	Cubic meter	4,901.33	3,000	6,500	23.55
Outputs	Desirable	Yield (stigma)	kg	8.39	5	12	18.42
	Undesirable	Carbon dioxide equivalent	kg	7,714.53	0	17,300.23	62.01

yield of stigmas harvested per hectare is considered as the desirable output.

2- **The carbon dioxide equivalent excess of inputs:** Due to the lack of comprehensive information on the net emission of GHG from saffron farms, the total carbon dioxide equivalent of GHG from the consumption of inputs was applied according to previous studies (Nemecek et al., 2011; Urdiales et al., 2016; Grassauer et al., 2021; Martinsson & Hansson, 2021). Since some of these inputs are absorbed by the plant, in this paper, only the excess consumption of polluting inputs is considered as undesirable output for each farm. Thus, this variable, instead of measuring the pollution potential of inputs, has been calculated according to the f excess farm consumption of these inputs. This indicates the effect of technical inefficiency of farms on the level of environmental pressure and the relationship between economic and environmental issues is emphasized.

2.4 Data processing

In order to calculate the undesirable output mentioned in the above paragraph, first, the envelopment analysis model of conventional output-oriented data was estimated and based on that, the excess consumption of inputs was calculated using the output and inputs referred in the research. Then, the excess carbon dioxide equivalent consumption of GHG emission inputs was calculated using the GHG conversion coefficients of each input and their sum was entered into the model as undesirable output. The GHG conversion ratio of the inputs used in this research is shown in Table 1.

A statistical description of the IOs defined above is given in Table 2. As mentioned earlier, the inputs used are divided into three categories of high-pollution, low-pollution and independent inputs, which are categorized according to the size of the GHG conversion coefficients of each input (Table 1). Thus, the inputs with a

TABLE 3 Results of TE and EEE of saffron producers in Ghaen County.

		TE	EEE
Statistical description of efficiency	Average	0.862	0.744
	Minimum	0.689	0.011
	Maximum	1	1
	Coefficient of variation	44.1	0.1738
	Fully efficient units	51 (22.60%)[a]	97 (42.90%)
Categorized efficiency	<0.2	0	14 (6.2%)
	0.2–0.5	0	35 (15.5%)
	0.5–0.8	61 (27%)	60 (26.5%)
	0.8–1	165 (73%)	117 (51.8%)

[a]The numbers in parentheses indicate the percentage of the DMUs.

conversion coefficient greater than 1 kg/unit are selected as high pollutant inputs and inputs with a conversion coefficient of less than 1 are low pollutant inputs. This classification enables the model to replace high-polluting with low-polluting inputs, in addition to minimizing the consumption of inputs (product maximization).

According to Table 2, among the inputs, the highest coefficient of variation is assigned to chemical fertilizers of potassium (277.96), phosphate (275.70) and nitrogen (79.78), and after seed input, animal manure has the highest variation coefficient. This can be due to the replacement of chemical fertilizers with each other and with animal manure in different farms. It is worth to mention that the carbon dioxide equivalent, which is considered as the potential of each unit in environmental pollution, also has a high coefficient of variation, which indicates the difference between the use of units of different inputs and with different polluting percentage. Therefore, it can be concluded that modifying the method by which units use different inputs and considering environmental factors, can have a significant effect on reducing environmental pollution.

3 Results

In this section, the results of estimating the EEE based on the model of Arabi et al. (2017) and also, the results of technical efficiency (TE) by non-radial SBM method are depicted in Table 3. According to the results, the average TE of saffron growers in Ghaen is equal to 86%, but by considering environmental pollution, their TE is reduced to 74%. In other words, neglecting environmental issues causes the efficiency of saffron producers to be calculated 12% higher than its actual value. The number of efficient units in the estimation of EEE and TE are 97 and 51 units, respectively. The efficiency of 46 additional units (97–51 = 46) in EEE shows that although these producers are inefficient considering only technical efficiency factors, when environmental issues are also considered, these units are efficient in terms of EEE. This means that even though these units have lower output production or higher input consumption, they have lower GHG emissions than the other units. In other words, the reduction in environmental pressure has compensated for the lack of product production or excess consumption of inputs. However, the average value of TE is higher than EEE, and the reason is that the number of units with an efficiency score below 50% is 0 and 49 units for TE and EEE, respectively. In other words, about 22% of the units have an efficiency score of less than 50% in EEE, which has caused a sharp decrease in this type of efficiency.

Then, the average of the actual and desired amount of consumption IOs produced was calculated using the deficits and excesses extracted from the models and the results are presented in Table 4. The percentage change of the average optimal consumption compared to the actual consumption of low-polluting inputs in the EEE model is positive. In other words, inefficient units should increase the consumption of these inputs in order to achieve efficiency. As expected, the percentage change in polluting inputs is negative and consumption of these inputs in inefficient units should be decreased. Among polluting inputs, nitrogen fertilizer has the highest change percentage, and inefficient units should reduce their nitrate fertilizer consumption by about 42% to achieve EEE.

Given that the slack-based models are not radial and calculate efficiency from both the maximization of outputs and the minimization of inputs, the excess or deficient amount of outputs can also be observed. In the SBM model, inefficient producers have the maximum production of saffron due to the consumption of inputs and the percentage of changes in the optimal production of saffron output is zero compared to the current production of producers. In the EEE model, the percentage of changes in saffron output is very small and indicates that the production of saffron is optimal, but in order to achieve this efficiency, Ghaen saffron growers should reconsider the consumption of input and, on average, reduce their carbon dioxide emissions by 7.27 percent. The percentage of changes in the consumption of inputs compared to the actual value obtained from the TE model indicates that the highest percentage of changes is assigned to the three inputs of phosphate, potassium, and nitrogen. The percentage change of the average optimal consumption was −91, −74 and −67 percent, respectively, in relation to their value for these three inputs. Therefore, without considering the amount of environmental pollution, farmers can greatly increase their TE by reducing the consumption of these three inputs. The lowest percentage of changes is assigned to three inputs of water (−22), fungicide (−26) and animal manure (−27).

TABLE 4 The average optimal consumption of inputs and the percentage of their changes to the actual consumption.

				TE		EEE	
			Actual value	Optimal value	Changes (%)	Optimal value	Changes (%)
Inputs	Low-Polluting	Potassium	5.67	1.46	−74.25	6.22	9.71
		Phosphate	11.17	1.02	−90.89	18.34	64.23
		Manure	32.19	23.51	−26.95	32.38	0.61
		Manpower	972	488	−49.77	981	0.91
		Electricity	22,383	12,278	−45.14	22,383	0.003
	High-Polluting	Nitrogen	62.37	20.89	−66.51	36.18	−41.99
		Fungicides	1.72	1.27	−26.24	1.32	−23.23
		Machinery	41.96	27.87	−33.59	30.74	−26.75
		Fuel	535.16	323.57	−39.54	359.66	−32.79
	Independent	Seed	5,682	2,349	−58.66	2,937	−48.30
		Water	4,901	3,816	−22.13	3,948	−19.43
Outputs	Desirable	Yield (stigma)	8.38	8.38	0	8.39	0.09
	Undesirable	Carbon dioxide equivalent	7,714	-	-	7,153	−7.27

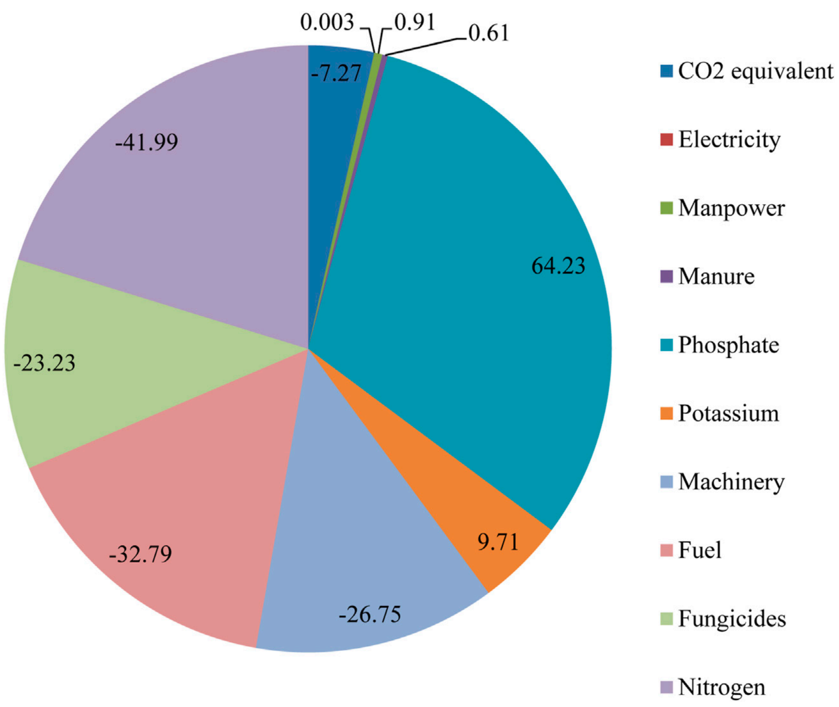

FIGURE 3
Percentage of changes in the optimal average of IOs relative to their actual value.

According to the results in Table 4, the highest percentage of changes in the average optimal consumption compared to the actual value was obtained from the EEE model regarding phosphate input. However, it should be mentioned that the average optimal amount of phosphate consumption in this model is higher than the average actual value. Thus, in order to increase their EEE, farmers should increase their consumption of the low-polluting input by 64%. However, for nitrogen fertilizer, which is a highly polluting input, farmers should reduce their consumption by 42% to achieve full efficiency. The third eco-inefficiency factor of input is seed, and

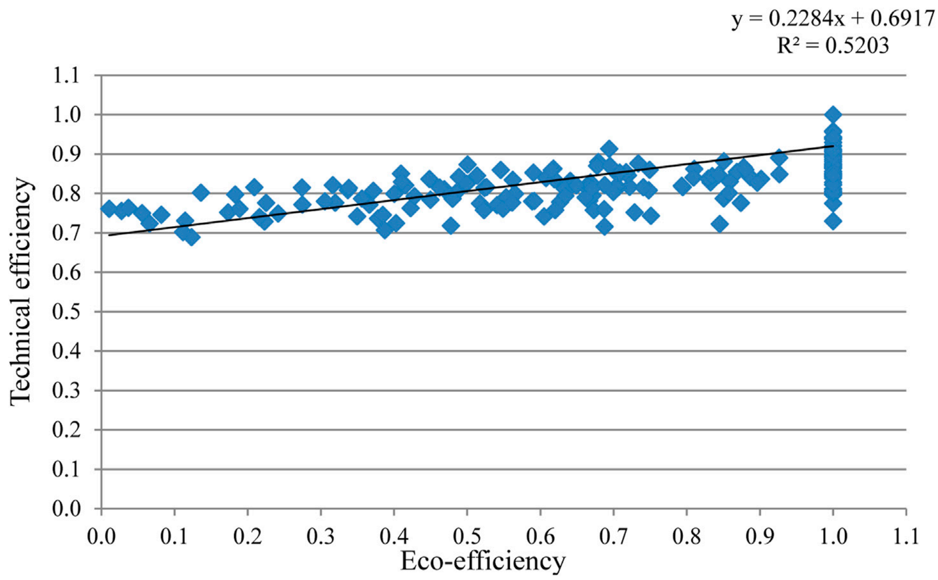

FIGURE 4
Relationship between TE and EEE.

farmers should reduce seed consumption by 48% to achieve efficiency. The optimal consumption of this input in the TE model was on average 58% lower than the average actual consumption. Also, the lowest percentage of changes was related to electricity, animal manure and labor inputs, and farmers had to increase the amount of these inputs as small 0.003, 0.61, and 0.91, respectively.

For better indication of the eco-inefficiency factors of inefficient units, the percentage change of pollutant inputs and undesirable output is shown in Figure 3. According to this figure, the most important factor of inefficiency of saffron producers in Ghaen Country is the shortage of phosphate fertilizer consumption and then the excess consumption of nitrogen fertilizer, diesel fuel and machinery. Also, on average, inefficient producers should reduce their carbon dioxide equivalent output by 7.27 percent. Among these inputs, electricity with a percentage change of 0.003%, manure (0.61), and labor (0.91), had the least effect on inefficiency of producers and should slightly increase the consumption of these inputs.

4 Discussion

In this study, the EEE was evaluated according to the GHG emission from agricultural activities in saffron cultivation. In this section, the results obtained from this model are investigated and compared with the results of studies performed in this field. According to the results, the resulting EEE is 12% lower than the TE of saffron growers and its average has reduced from 86% to 74%. In other words, without considering the environmental issues and GHG emissions associated with crop production, TE is estimated to be 12% higher than actual value. In addition, the minimum efficiency obtained in the TE model is 68% and is 1% in the EEE model, and even 22% of the units in this model have an efficiency of less than 50%. Also, the difference in indicating the number of units with the efficiency higher than 80% is 22%. This means that 48 units represent efficiencies above 80% by mistake, regardless of environmental pressure. Absolute attention to producing the maximum possible output using the minimum input may lead to maximum technical efficiency for DMUs, but this action may increase the amount of environmental pressure and lead to low EEE. Therefore, in estimating EEE, inputs with less pollution are replaced by inputs with high pollution.

According to the results of calculating the deficiency and excess consumption of inputs and production of outputs from the SBM-based models, in both models of TE and EEE, chemical fertilizers were the most important factors of unit inefficiency. However, in the first model, phosphate and potassium fertilizers should be reduced and in the second model, they are increased. This is logical as phosphate and potassium fertilizers produce less GHG than highly polluting inputs such as nitrogen. In other words, these inputs replace high-polluting inputs to reduce the damage to the environment (undesirable output) by keeping or increasing the economic value of the activity (desirable output). In a study done by Picazo-Tadeo et al. (2011), Nitrogen has been one of the most important causes of eco-inefficiency of the studied farmers. It is worth to mention that considering different indicators for measuring environmental pressure also leads to different EEE outcomes (Grassauer et al., 2021). For example, the present study emphasizes on reducing nitrogen input and increasing the input of phosphate fertilizers in order to reduce GHG emissions, but if the phenomenon of Eutrophication is considered as an indicator of environmental pressure, as phosphate fertilizers are effective on this index (Khoshnevisan, Rafiee, et al., 2013b), different results may be obtained. However, the amount of phosphate fertilizer in the studied saffron farms (average, 11.7 kg/ha) is less than this amount in studies on other areas (Feizi et al., 2015).

In the EEE model used in this study, it is attempted to change the way of using inputs and replace high-polluting inputs with low-polluting inputs, while maintaining the desirable output as possible, the GHG emissions can be reduced. As shown in Table 4, the average optimal amount of production by considering the environmental pressure, has been approximately equal to this rate in the conventional efficiency model. However, to achieve optimal efficiency, inefficient units should, on average, reduce the carbon dioxide equivalent produced from their GHG as 560.81 kg (27.7%). This change is achieved by replacing high-polluting inputs with low-polluting inputs. Therefore, in the conventional TE model, the percentage change of the optimal average consumption value is lower than the actual consumption value of all inputs, while in the EEE model, this value is increasing for low-polluting inputs and decreasing for high-polluting inputs. Therefore, in order to achieve full efficiency, inefficient farmers should reduce their consumption of polluting inputs such as nitrogen, diesel fuel machines and fungicides, and instead increase the use of electricity, manpower, animal manure, phosphate and potassium inputs.

The relationship between TE and EEE is depicted in Figure 4. According to this figure, the correlation between TE and EEE has been positive. Also, among the rankings obtained from the two calculated efficiency criteria, Spearman coefficient was equal to 0.775 and significant at the level of 1%. Therefore, as mentioned before, EEE only calculates and analyzes the relative pressure on the environment, and the amount of reduction in polluting inputs should be higher than the amount calculated. Indeed, this criterion by considering economic issues along with environmental issues, is an easier and more appropriate approach to be used by policy makers. This is especially evident in third world countries with lower levels of economic prosperity.

5 Conclusion

Considering the importance of the environmental sustainability conservation, this study aimed to calculate the EEE of saffron growers in Ghaen County in Iran. Given the importance of compliance with the requirements of the MBP in estimating the EEE, the efficiency model consistent with the MBP of Arabi et al. (2017) was used and the amount of GHG emissions (carbon dioxide equivalent) was used as an undesirable output in this model. Unlike the conventional DEA model, in these models, farm efficiency is also affected by environmental variables, besides the economic variables, and the units have EEE that in addition to maximum production, and using the minimum input, can create the least environmental pollution. Comparing the results of the mentioned model with the conventional SBM model showed that there is a difference of 12% between the average EEE and TE. Therefore, not considering the environmental issues in estimating efficiency presents incorrect results and leads to the continuation of inefficient and unorganized use of inputs. Another result of this study is that the inconsistent use of chemical fertilizers of phosphate and nitrogen with the environment has been one of the most important eco-inefficiencies of saffron growers in the study area. This indicates the importance of using fertilizers correctly and replacing them with manure. In addition, high diesel fuel consumption is the second cause of eco-inefficiency. The main reason for this is the use of old machines, disproportionate to the cultivation level in saffron farms in Iran, and in order to achieve sustainable cultivation of this crop, we should modify the equipment used in the cultivation of this product. Field, 1994.

Data availability statement

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

Author contributions

All authors contributed to the study conception and design. Material preparation and analysis were performed by, MM and FR. The first draft of the manuscript and data collection were written by FY and EA and all authors commented on previous versions of 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

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Variations of soil properties and soil surface loss after fire in rotational shifting cultivation in Northern Thailand

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Since fire is still necessary for rotational shifting cultivation (RSC), the vertical distribution and slope effect on soil properties and soil surface loss after a fire remain unclear. To address these research gaps, the study aims to achieve the following objectives: 1) investigating post-fire soil properties and soil surface loss in RSC, and 2) assessing the vertical distribution and slope effect on soil properties and soil surface loss in RSC. Soil samples were collected from two stages of RSC: 6 years (RSC-6Y) and 12 years (RSC-12Y), located in Chiang Mai Province, Northern Thailand. A continuous 15-year left fallow field (CF-15Y) was used as the reference site. Soil samples were collected from the upper, middle, and lower slopes at depths of 0–5, 5–10, 10–20, and 20–30 cm at five different time points: before burning, 5 min, 3 months, 6 months, and 9 months post-fire. The results indicated that older fallow fields had a tendency to accumulate more soil organic carbon (SOC) and soil organic nitrogen (STN). The color of the ash was altered by the fire, resulting in dark reddish-brown ash with higher levels of pH, organic matter (OM), electrical conductivity, total nitrogen, and soil nutrients when compared to gray and white ashes. The combustion of OM during the fire was found to release soil nutrients, which could explain the increase after burning. SOC stock increased at deeper layers (5–10 cm) with higher values than pre-burning levels, especially at lower slope positions, while STN stock decreased at the surface soil post-fire but increased in deeper layers at all slope positions. The average soil surface loss ranged from 1.6 to 3.1 cm, with the highest loss observed 9 months after the fire (during the rainy season) at the upper slope. In terms of the impact of slope on soil properties following the fire event, our study indicated a significant correlation between lower slopes and variables including SOC, STN, electrical conductivity, nitrate–nitrogen (NO_3-N), ammonium nitrogen (NH_4-N), exchangeable calcium, and exchangeable magnesium. Further study is required to investigate and develop appropriate post-fire management strategies to effectively reduce nutrient loss and minimize soil surface erosion.

KEYWORDS

rotational shifting cultivation, soil organic carbon, soil total nitrogen, soil loss, fire

1 Introduction

Shifting cultivation is indeed one of the most complex and diverse forms of agriculture globally, with multiple aspects of land use systems developing since as early as 10,000 BC (Thrupp et al., 1997). The hill tribe population in Thailand traditionally depends on shifting agriculture. Prior to the 1960s, two major types of shifting cultivation were commonly practiced: pioneer and rotational. The pioneer shifting system was practiced by Hmong, Lahu, Lisu, Akha and Yao tribes, where fields were cleared, burned, and cropped until crop production decreased, indicating low soil fertility. People then abandoned the fields and relocated to a new site. In the rotational system, fields were cut, burned, cropped for one season, abandoned for recovery, and then returned for cropping, usually practiced by Karen and Lua tribes (Bass and Morrison, 1994; Rerkasem and Rerkasem, 1994). Currently, the practice of pioneer shifting cultivation has been restricted to forested areas due to the increase in population density and forest conservation policy, which have made this practice impossible in Thailand. Moreover, voluntary village relocation is extremely rare, and long fallow shifting cultivation has mostly disappeared. As a result, shifting cultivation in Thailand now mainly consists of the rotational system (Arunrat et al., 2022a; 2023).

The practice of rotational shifting cultivation (RSC) is reported to cause anthropogenic forest disturbances and soil degradation (Curtis et al., 2018), as it reduces both above and below ground biomass from natural vegetation (van Straaten et al., 2015). Furthermore, the use of fire for land preparation in RSC can have a negative impact on the topsoil (Pennington et al., 2001). Fire tends to decrease soil carbon by burning organic matter (OM) and reducing OM inputs (Jhariya and Singh, 2021), leading to reduced soil water and available nutrients (Phillips et al., 2000). After a fire, soil pH and electrical conductivity (ECe) often increase (Arunrat et al., 2021). Lauber et al. (2009) revealed that soils with close to neutral pH typically exhibit higher bacterial diversity compared to more acidic or basic soils. Additionally, soil nitrogen can be lost through volatilization (Zavala et al., 2014), which in turn can decrease soil microbial activity (Fierer et al., 2012). However, Christensen and Muller (1975) indicated that a rapid increase in nitrogen mineralization rates can promote increased microbial activity during the initial post-fire periods. Post-fire soil nutrients can be lost through leaching, soil erosion, and runoff (Faria et al., 2015), or increased from chars and ashes (Alcañiz et al., 2016). A reduction in the fallow cycle can cause a decline in soil fertility, increase soil loss, and decrease crop production. Gafur et al. (2000) found that approximately 27% of the soil nutrients were removed from the topsoil (10 cm) due to soil loss in shifting cultivation in Bangladesh, while these nutrients were deposited in the watershed. Mishra and Ramakrishnan (1983) investigated total sediment yields in shifting cultivation in northeastern India and found 49.7 and 56.3 t ha^{-1} $year^{-1}$ in 10 and 5 fallow years, respectively. Thus, the changes in soil surface after a fire need to be investigated, but there is still a lack of studies on this aspect in Thailand.

Soil organic carbon (SOC) serves as both a source and sink of CO_2, storing the largest pool in terrestrial ecosystems, which is two-thirds larger than the atmosphere (Smith, 2004). Lal (2003) revealed that even a small percentage change in soil carbon can significantly alter CO_2 concentrations in the atmosphere. However, RSC and shortened cultivation cycles have been shown to have negative impacts on soil fertility, OM content, and erosion occurrence (McDonald et al., 2002; Gafur et al., 2003). Wairiu and Lal (2003) used SOC concentration as an indicator for soil erosion on sloping lands, showing that slash-and-burn agriculture resulted in higher losses of SOC in the topsoil than natural forest due to strong erosion. On the other hand, previous studies have reported the positive effects of biochar and ash after fire, which can increase SOC, soil fertility, and crop productivity (Lehmann et al., 2003; Dempster et al., 2012; Agegnehu et al., 2015; Reed et al., 2017; Moragues-Saitua et al., 2023). Although soil erosion can lead to carbon loss in eroded areas (Haj-Amor et al., 2022), it can also induce carbon sink due to the movement of carbon from eroded soil surface areas to depositional positions (Van Oost et al., 2007). Moreover, SOC can be transported to deeper soil layers due to intrinsic factors (e.g., climate, parent material, and topography) and extrinsic factors (e.g., vegetation, practice, and land use) (Teng et al., 2017). Deep SOC is important because it has a high potential for storage, with unsaturated carbon concentrations and slow turnover times (Trumbore, 2009). It has been reported that most deep SOC comes from vertical transport of dissolved organic carbon, carbon input by root penetration, and clay-bound organic carbon (Rumpel and Kögel-Knabner, 2011). However, the vertical dynamics of SOC and soil nutrients at the soil surface (0–30 cm) in RSC remain poorly understood. This lack of understanding is attributed to the fact that most of the root zone of upland rice is typically concentrated at the soil surface in RSC.

To this end, understanding the variations in soil properties and soil surface loss in RSC is crucial for assessing dynamics and developing appropriate management strategies. A fallow period is necessary for recovering soil nutrients; however, it is unknown how long it takes to reach the initial level, as it varies depending on factors such as topography, weather conditions, soil types, and land management. To date, there are limited studies on soil properties and soil surface loss before and after burning in RSC in Thailand. Furthermore, the variation of soil properties and soil surface loss throughout the cultivation cycle has not been reported. Therefore, the objectives of this study are 1) to investigate post-fire soil properties and soil surface loss in RSC and 2) to assess the vertical distribution and slope effect on soil properties and soil surface loss in RSC. This study provides the crucial knowledge on soil properties and soil surface loss dynamics, leading to the development of proper post-fire land management strategies in RSC.

2 Material and methods

2.1 Study area and field selection

The research was carried out in Ban Mae Pok, Ban Thab Subdistrict, Mae Chaem District, Chiang Mai Province, located in Northern Thailand, as shown in Figure 1. The study sites are situated in a mountainous area, with an elevation ranging from 700 to 1,000 m a.s.l. The rainy season usually starts from May until October. Winter season occurs from October to February, whereas summer season is from February to May (Trisurat et al., 2010; Department of Mineral Resources, 2015). Based on data from the Thai Meteorological Department's weather stations in Doi Ang

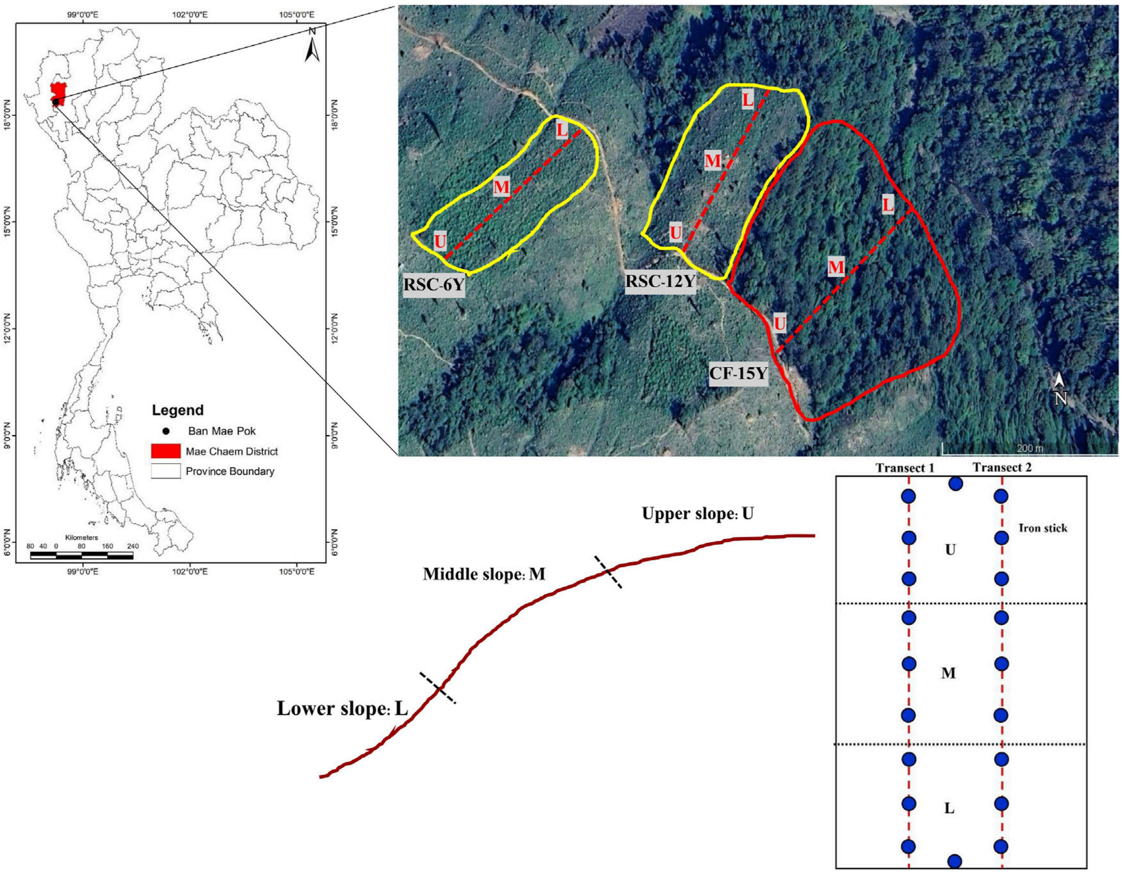

FIGURE 1
Study area. The aerial image was taken from Google Earth on 29 July 2023.

Khang and Mueang Chiang Mai, the total rainfall during March to December 2022 was 2,227.5 mm. The highest amount of rainfall occurred in September (525.6 mm), while the lowest was recorded in November (16.0 mm). Soils in the highlands of Thailand (with slopes greater than 35%) are classified as slope complex series, which mostly includes mountainous areas (LDD, 1992; USAID, 1993). The topsoil (0–10 cm) is sandy loam, and the subsoils (10–30 cm) are sandy clay loam and sandy loam, mostly composed of reddish-brown lateritic soil. The soil pH varies from 5.63 to 6.65, and the OM content ranges from 2.75% to 5.53% (Arunrat et al., 2022a).

In this study, two RSC fields were selected, which were previously used for upland rice cultivation and then left fallow to allow for the recovery of secondary forest vegetation (Figure 1). The RSC-12Y (18°23′12.03″N, 98°11′39.56″E), at an elevation of 692 m a.s.l and with a slope gradient of 28% was left fallow for 12 years after upland rice harvesting, and in 2022, it was cleared, burnt, and cultivated with upland rice. The RSC-6Y (18°23′11.5″N, 98°11′33.56″E), at an elevation of 729 m a.s.l and with a slope gradient of 31% was left fallow for 6 years after upland rice harvesting, and in 2022, it was also cleared, burnt, and cultivated with upland rice. We also used a reference site, the 15-year continuous left fallow (CF-15Y) (18°23′10.11″N, 98°11′44.29″E), at an elevation of 640 m a.s.l and with a slope gradient of 30%, where no cultivation or burning was carried out and the soil properties continued to recover naturally.

To grow upland rice in RSC-6Y and RSC-12Y fields, upland rice seeds (~125.0 kg ha^{-1}) were dropped by hand using spades or planting sticks to dig shallow holes. The water source was rainfall only. Upland rice was harvested by hand, and the residues were left in the fields. The fields were then abandoned to allow for the recovery of secondary forest vegetation.

2.2 Experimental design and fire measurements

In 2022, the RSC-12Y (75 m × 170 m) and RSC-6Y (45 m × 150 m) fields were selected to cultivate based on the village rotation cycle. The boundaries of each RSC field were marked, and grasses, shrubs, woods, and saplings were cut and left in the field to dry in the sunlight for around 30–45 days. Firebreaks were created around the fields with a width of 5–7 m to prevent the spread of fire during burning. Each RSC field was divided into three slope positions - upper slope, middle slope, and lower slope (Figure 1). At each RSC field, the 20 iron sticks (30 cm length) with label scale were installed in 20 positions to measure the soil surface changes by installing at 0 cm of soil surface. Two transects were established vertically, spanning from the upper to the lower slope positions, and nine additional transects were marked horizontally. At the intersection of these vertical and horizontal transects, iron sticks were installed, with spacing of approximately 35 m × 20 m and 25 m × 15 m for RSC-12Y and RSC-6Y, respectively (Figure 1). Three plots were marked for measuring fire temperature, soil temperature, and soil sampling.

The burning of the RSC fields started at 3:00 p.m. and ended at around 5:00 p.m. after obtaining permission from the Mae Chaem District Office. During the burning process, the fire temperature at each pit of each RSC field was measured using an infrared thermometer (PONPE 470IR). Soil temperature and moisture were measured before (pre-burning) and 5 min after burning at each pit of each RSC field at the depth of 5, 10, 20, and 30 cm using a Thermocouple Type K (PONPE 422 PR) and moisture meter, respectively. The fire temperature, soil temperature, and soil moisture of RSC fields were presented in Supplementary Table S1.

2.3 Soil and ash sampling and analysis

Soil samples were collected from the upper slope, middle slope, and lower slope of RSC-12Y and RSC-6Y fields at depths of 0–5, 5–10, 10–20, and 20–30 cm at five different time points: before burning (March 2022), 5 min after burning (March 2022), 3 months after burning (June 2022), 6 months after burning (September 2022), and 9 months after burning (harvest, December 2022). Soil samples from the CF-15Y field were collected at four time points: March 2022, 3 months after RSC fields burning, 6 months after RSC fields burning, and 9 months after RSC fields burning.

A total of 360 soil samples were collected from the RSC fields, with 2 RSC fields, 3 plots, 4 depths, 5 time points, and 3 slope positions. In addition, 48 soil samples were taken from the CF-15Y site, with 1 CF site, 3 plots, 4 depths, and 4 time points. At each slope position of each RSC field, soil samples were collected from the same three plots at each time point. At each plot (20 × 20 m), soil samples of each depth were taken from five pits and mixed to obtain one composite sample per depth per plot. Stones, grasses, roots, and residues were removed manually, and around 1 kg of soil was placed in a plastic bag. Ash colors were determined using the Munsell soil color charts after the fire. A steel spoon was used to meticulously collect ash of each color from the respective sample plots. The chemical properties of ash were provided in Supplementary Table S2. Furthermore, a steel soil core (5.0 cm width × 5.5 cm length) was used to collect a soil sample from each depth to determine soil bulk density after drying at 105 °C for 24 h.

Soil texture was determined using the hydrometer method, while soil pH and ash pH were measured using a pH meter with a 1:1 and 1:10 suspension of solids in water, respectively (National Soil Survey Center, 1996). Electrical conductivity (ECe) was determined by measuring the saturation paste extracts using an EC meter (USDA, 1954). The cation exchange capacity (CEC) was measured by the NH_4OAc pH 7.0 method. Total nitrogen (TN) was analyzed using the micro-Kjeldahl method. Ammonium nitrogen (NH_4-N) and nitrate–nitrogen (NO_3-N) were measured by the KCL extraction method. The exchangeable calcium (exch.Ca), magnesium (exch.Mg), and potassium (exch.K) values were analyzed using atomic absorption spectrometry with NH_4OAc pH 7.0 extraction. Available phosphorus (avail.P) was measured using the molybdate blue method (Bray II extraction) (Bray and Kurtz, 1945). Organic carbon (OC) content was analyzed following the method of Walkley and Black (1934) using potassium dichromate ($K_2Cr_2O_7$) in sulfuric acid, and the results were reported as organic matter (OM) by multiplying with 1.724.

2.4 Soil organic carbon and total nitrogen estimation

The SOC stock was estimated using the following equation:

$$SOC_{stock} = \sum_{i=1}^{n} (BD_i \times L_i \times OC_i \times 10,000) \quad (1)$$

where SOC_{stock} is the soil organic carbon stock (Mg C ha^{-1}), OC_i is the organic carbon content (%), BD_i is the soil bulk density (Mg m^{-3}), L_i is the soil thickness m), and i represents the ith layer.

The STN stock was calculated using the following equation:

$$STN_{stock} = \sum_{i=1}^{n} (BD_i \times L_i \times TN_i \times 10,000) \quad (2)$$

where STN_{stock} is the soil total nitrogen (Mg N ha^{-1}), TN_i is the total nitrogen content (%), BD_i is the soil bulk density (Mg m^{-3}), L_i is the soil thickness m), and i represents the ith layer.

To eliminate the potential impact of varying soil bulk density over time, which could lead to errors in estimating SOC stock, we employed the equivalent soil mass approach (Ellert and Bettanym, 1995) to adjust the SOC stock calculations using the following equation:

$$Soil\,mass = BD \times L \quad (3)$$

where $Soil\,mass$ is the mass of the soil sample (kg soil m^{-2}).

The adjusted soil thickness m) for each RSC field was calculated using the following equation (Arunrat et al., 2021):

$$\text{Adjusted soil thickness} = \frac{Mass_{initial} - Mass_{end}}{BD} \quad (4)$$

where $Mass_{initial}$ is the soil mass at the commencement of the study (March 2022), and $Mass_{end}$ is the soil mass at the end of study (December 2022).

2.5 Soil surface loss measurement

At each RSC field, the level of soil surface changes was recorded by measuring the label scale on 20 iron sticks. The 0 cm of soil surface level was recorded before burning in March 2022, and the label scales were recorded again at 5 min after burning in March 2022, 3 months after burning in June 2022, 6 months after burning in September 2022, and at harvest in December 2022. For the CF-15 site, a total of 20 iron sticks were also installed to monitor the level of soil surface at four time points: March 2022, 3 months after RSC fields burning, 6 months after RSC fields burning, and 9 months after RSC fields burning.

2.6 Statistical analysis

Statistical analysis was performed using the R environment (v.4.0.2). Soil physiochemical properties were compared among

TABLE 1 Variation in soil properties: bulk density (BD) (Mg m^{-3}), electrical conductivity (EC_e) (dS m^{-1}), organic matter (OM) (%), organic carbon (OC) (%), total nitrogen (TN) (%), and proportion of sand, silt and clay (%) with land use, position, soil depth, and chronological time of burning.

Variable	Category		pH (1:1)		EC_e		BD		OM		OC		TN		%Sand		%Silt		%Clay	
			Mean	std	Mean	std	Mean	std	Mean	std	Mean	std	Mean	std	Mean	std	Mean	std	Mean	std
RSC field	CF-15Y		4.83^{b}	0.02	0.12^{c}	0.11	1.36^{b}	0.05	4.27^{a}	0.28	2.47^{a}	0.16	0.23^{a}	0.07	26.43^{a}	4.41	45.55^{b}	3.88	28.03^{a}	7.09
	6-year fallow		5.37^{a}	0.15	0.23^{b}	0.26	1.40^{a}	0.06	3.34^{b}	0.26	1.94^{b}	0.15	0.13^{c}	0.04	17.42^{b}	4.35	45.89^{b}	6.23	36.70^{b}	8.72
	12-year fallow		5.25^{a}	0.18	0.33^{a}	0.30	1.35^{c}	0.05	3.49^{b}	0.29	2.02^{b}	0.17	0.17^{b}	0.07	20.40^{c}	4.31	47.46^{a}	3.79	32.17^{c}	7.11
Position	Lower slope		5.46^{a}	0.03	0.32^{a}	0.32	1.37	0.06	3.74^{a}	0.28	2.17^{a}	0.16	0.17^{a}	0.06	19.53^{a}	3.99	46.33^{b}	5.06	34.14^{a}	7.40
	Middle slope		5.17^{b}	0.02	0.20^{b}	0.21	1.37	0.06	3.33^{b}	0.04	1.93^{b}	0.02	0.13^{b}	0.05	19.24^{a}	4.43	47.68^{a}	5.19	33.10^{b}	7.75
	Upper slope		5.30^{b}	0.07	0.33^{a}	0.30	1.38	0.06	3.18^{b}	0.16	1.84^{b}	0.09	0.15^{a}	0.07	18.17^{b}	5.11	46.05^{b}	5.14	35.80^{c}	9.20
Soil depth	0-5 cm		5.49^{a}	0.48	0.45^{a}	0.38	1.31^{d}	0.04	6.52^{a}	1.49	3.78^{a}	0.86	0.22^{a}	0.09	24.45^{a}	5.08	50.90^{a}	3.03	24.68^{a}	4.38
	5-10 cm		5.10^{b}	0.15	0.21^{b}	0.14	1.36^{c}	0.04	3.87^{b}	0.52	2.25^{b}	0.30	0.20^{a}	0.07	20.48^{b}	4.50	49.08^{a}	3.13	30.47^{b}	3.60
	10-20 cm		4.92^{b}	0.58	0.14^{c}	0.08	1.40^{b}	0.05	2.56^{c}	0.04	1.49^{c}	0.02	0.15^{b}	0.04	19.30^{bc}	3.53	45.54^{b}	2.63	35.16^{c}	4.32
	20-30 cm		5.08^{b}	0.12	0.11^{c}	0.05	1.41^{a}	0.05	1.85^{d}	0.08	1.07^{d}	0.05	0.13^{c}	0.03	16.02^{d}	4.03	40.60^{c}	3.60	43.38^{d}	6.52
Condition	Pre-burning		4.98^{D}	0.14	0.12^{D}	0.08	1.36^{B}	0.05	3.71^{C}	0.70	2.15^{C}	0.41	0.19^{A}	0.07	20.15^{A}	5.33	46.19^{C}	4.35	33.66^{C}	8.34
	Post-burning	5 mins	5.46^{A}	0.10	0.25^{C}	0.27	1.36^{B}	0.06	3.09^{D}	0.15	1.79^{D}	0.09	0.17^{AB}	0.08	20.20^{A}	5.86	46.35^{C}	4.46	33.53^{C}	8.94
		3 months	5.31^{C}	0.31	0.31^{B}	0.29	1.35^{B}	0.05	3.71^{C}	0.68	2.15^{C}	0.40	0.16^{C}	0.04	17.98^{C}	3.63	48.24^{A}	5.63	33.78^{C}	8.07
		6 months	5.15^{C}	0.28	0.36^{A}	0.32	1.35^{B}	0.05	3.73^{B}	0.22	2.16^{B}	0.13	0.18^{BC}	0.05	18.16^{C}	3.67	47.28^{B}	5.52	34.56^{B}	8.00
		9 months	5.18^{B}	0.34	0.37^{A}	0.32	1.43^{A}	0.05	3.87^{A}	0.23	2.24^{A}	0.14	0.10^{D}	0.03	18.52^{B}	3.74	45.38^{D}	5.30	36.09^{A}	7.86

$^{a\text{-}e,\ A\text{-}E}$ Uppercase letters denote significant statistical differences ($p \leq 0.05$), as analyzed by using One-way ANOVA and repeated measures One-way ANOVA with post-hoc Tukey's HSD

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the CF-15, RSC-6Y, and RSC-12Y sites with varying positions and soil depths using Analysis of Variance (ANOVA). When the ANOVA result was significant at $p \leq 0.05$, the Tukey Honestly Significant Difference (HSD) test was employed to perform multiple *post hoc* mean comparisons. The effect of the area position on soil properties was explained by Redundancy Analysis (RDA). The impact of each RSC field's slope position on soil properties was analyzed using RDA, focusing on the position-based variation rather than individual layers. To ensure the integrity of our analysis, all explanatory variables underwent transformation and standardization through the application of the Hellinger method. Addressing concerns related to non-significant variables and collinearity, we adopted the forward selection method for variable selection. The R packages "tidyverse," "agricolae," "vegan," "fastDummies," and "ggplot2" were used for data arrangement, ANOVA and *post hoc* tests, data transformation, and data visualization.

3 Results

3.1 Variation of soil physical properties

The soil bulk densities among all fallow soils exhibited significant differences, with RSC-6Y showing the highest bulk density at 1.40 Mg m^{-3}. The OM percentage was notably elevated in CF-15Y, while no significant difference in OM content was observed between the remaining RSC-6Y and RSC-12Y fields. Silt content was highest across all fallow soils, whereas the clay percentage in RSC-6Y was comparatively elevated compared to the other two sites (Table 1).

The topography positions have an impact on the soil physical properties in all RSC fields. The highest OM content was observed in the lower slope with 3.74%. Among the three types of soil particles, silt occupied the largest portion, and it was the richest in the middle slope with 47.68%. The percentages of sand in the lower and middle slopes were not significantly different, while the highest percentage of clay was found in the upper slope (Table 1).

The levels of OM exhibited significant differences after burning, displaying a pronounced decrease after 5 min of burning. Subsequently, there was a significant increase that persisted until 9 months after the fire, surpassing the pre-fire levels. However, soil bulk density and soil texture remained unaltered following the fire (Table 1).

3.2 Variation of soil chemical properties

The variation in soil chemical properties is influenced by the differences in fallow period. While CF-15Y exhibited a low pH value of 4.83, there was no significant difference in pH between RSC-6Y and RSC-12Y. It is important to note that there was a notable difference in ECe among the three types of fallow soil. TN had the highest proportion in CF-15Y, while its content was comparatively lower in RSC-6Y (Table 1). CEC was significantly higher in CF-15Y compared to RSC-6Y and RSC-12Y. There was no significant difference in available P between CF-15Y and RSC-6Y, while its content varied significantly in the 6- and 12-year fallow soils. Available K was most abundant in RSC-12Y, whereas RSC-6Y exhibited the highest available Ca content. Additionally, available Mg content was significantly higher in RSC-6Y compared to the other two types of fallow soil. It is worth mentioning that NH_4-N and NO_3-N levels differed significantly between CF-15Y and RSC-6Y, with both constituents being most abundant in RSC-12Y (Table 2).

Topography, especially hillslopes, can have a significant impact on soil chemical properties. Soil pH was observed to be highest in the lower slope, whereas ECe exhibited relatively lower values in the middle slope. TN content was comparatively lower in the middle slope (Table 1). The upper slope had the highest concentration of available P, while the middle slope exhibited comparatively lower levels of available K. Available Ca and Mg were most abundant in the lower slope (Table 2).

After burning, the soil pH showed a significant increase at the 5-min post-burning stage, reaching a value of 5.46. The highest ECe was observed 9 months after burning. TN content exhibited a continuous decline after the fire (Table 1). Available P content was notably high 5 min after burning, with a value of 11.18 mg kg^{-1}, while a remarkably high level of available K was found at the 3-month post-burning stage. Notably, available Ca contents in all post-burning stages displayed significant differences. A significant increase in available Mg was observed 3 months after burning, reaching a value of 100.51 mg kg^{-1}. Both NH_4-N and NO_3-N contents in all post-burning stages were also significantly different (Table 2).

3.3 Variation of soil organic carbon and soil total nitrogen stocks

The results of the ANOVA analysis indicated that there were significant differences in SOC and STN due to various factors, including RSC field, time point, topography position, and soil depth (Table 3). Significant differences in STN were observed for all individual variables, except for the interaction with the topography position. This indicates that the effect of each variable is not dependent on the topography level, and each variable has a separate impact on STN (Table 3).

SOC and STN levels can exhibit seasonal variability due to a range of factors across different slope positions. In CF-15Y, the SOC was highest at the 3-month stage after the fire, measuring 90.30 Mg C ha^{-1}, while it was lowest at the 6-month stage (Figure 2; Table 4). Across all slopes of RSC-12Y, there was no significant difference in SOC between the pre-burning stage and the 5-min post-burning stage. However, in the three slopes of RSC-12Y, the highest SOC was observed at the 9-month post-burning stage. The amount of SOC was notably high in the lower slope of the RSC-6Y field 9 months after burning, totaling 95.48 Mg C ha^{-1} (Figure 3; Table 4). In CF-15Y, there was no significant difference in STN between the 3-, 6-, and 9-month stages, but the highest STN was recorded at the 9-month stage, reaching 10.16 Mg N ha^{-1}. Among the three slopes of RSC-12Y, the STN was highest at the 6-month post-burning stage (Figure 4; Table 5). Notably, the STN was remarkably high in the middle slope of RSC-6Y at the 5-min post-burning stage (Figure 5; Table 5).

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TABLE 2 Variation in soil properties: cation exchange capacity (CEC) (meq 100 g^{-1}); available P (mg kg^{-1}); exchangeable K, Ca, and Mg (mg kg^{-1}), NH_4-N, and NO_3-N (mg kg^{-1}) content with land use, position, soil depth, and chronological time of burning.

Variable	Category		CEC		Avail. P		Exch. K		Exch. Ca		Exch. Mg		NH_4-N		NO_3-N	
			mean	std	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std
RSC field	CF-15Y		13.29^{a}	3.26	3.16^{b}	3.35	135.90^{b}	61.85	106.67^{b}	133.94	61.12^{b}	67.76	18.83^{b}	6.90	11.73^{b}	4.68
	6-years fallow		9.22^{b}	2.59	5.62^{b}	9.18	140.12^{b}	67.91	234.80^{a}	272.62	93.86^{a}	64.81	15.03^{b}	11.40	10.28^{b}	7.24
	12-years fallow		9.01^{b}	1.98	8.50^{a}	15.92	156.20^{a}	91.96	115.92^{b}	152.14	69.84^{b}	53.27	23.89^{a}	20.22	19.21^{a}	20.19
Position	Lower slope		9.10	2.0	6.39^{ab}	7.53	129.58^{b}	69.02	206.21^{a}	296.45	82.20	65.77	22.08	19.74	19.72^{a}	24.21
	Middle slope		9.13	2.24	6.00^{b}	11.69	124.82^{b}	75.36	170.05^{ab}	215.10	79.70	68.58	18.30	18.37	11.96^{b}	8.69
	Upper slope		9.08	2.64	9.00^{a}	17.70	189.02^{a}	82.90	146.96^{b}	149.85	82.50	44.59	18.71	12.59	13.50^{b}	10.52
Soil depth	0-5 cm		11.73^{a}	3.60	17.72^{a}	19.84	216.01^{a}	89.91	426.15^{a}	287.01	153.13^{a}	62.42	33.83^{a}	24.70	22.27^{a}	25.34
	5-10 cm		9.45^{b}	2.15	5.23^{b}	6.24	137.91^{b}	60.79	124.84^{b}	86.88	76.59^{b}	43.02	17.90^{b}	9.37	15.40^{b}	10.00
	10-20 cm		8.63^{b}	1.78	2.01^{c}	1.55	114.58^{c}	43.80	62.45^{c}	41.12	46.26^{c}	27.74	13.59^{c}	5.01	11.08^{c}	5.79
	20-30 cm		8.61^{b}	2.0	1.26^{c}	1.10	117.86^{c}	68.11	40.61^{c}	21.09	37.83^{c}	22.31	12.68	4.43	8.99^{c}	3.99
Condition	Pre-burning		9.78	2.27	1.42^{E}	1.48	138.28^{D}	67.54	112.39^{E}	113.07	65.70^{C}	43.21	14.80^{E}	7.80	14.71^{D}	26.30
	Post-burning	5 mins	10.68	3.05	11.18^{A}	15.72	171.72^{B}	100.43	228.79^{A}	293.68	90.37^{B}	67.79	21.44^{B}	22.10	8.65^{E}	8.18
		3 months	9.81	2.53	9.46^{B}	17.09	177.65^{A}	84.36	219.11^{B}	279.63	100.51^{A}	72.37	24.87^{A}	20.83	16.98^{B}	12.54
		6 months	9.04	1.60	8.77^{C}	14.37	157.56^{C}	75.06	192.38^{C}	232.80	92.75^{B}	62.50	20.73^{C}	15.17	17.86^{A}	12.39
		9 months	8.25	1.44	5.61^{D}	9.20	100.83^{E}	48.04	123.12^{D}	149.00	59.36^{D}	40.00	16.55^{D}	15.38	15.27^{C}	12.01

$^{a\text{-}e,\ A\text{-}E}$ Uppercase letters denote significant statistical differences ($p \leq 0.05$), as analyzed by using One-way ANOVA and repeated measures One-way ANOVA with post-hoc Tukey's HSD

TABLE 3 Results of one-way repeated measures ANOVA for soil organic carbon (SOC) and total nitrogen (STN) according to RSC field, time point, topography position, soil depth, and their interactions among variables

Variable	df	SOC			STN		
		MSE	*F*	*p*	MSE	*F*	*p*
RSC field (L)	2	117.30	48.05	***	15.47	218.31	***
Time point (T)	4	398.20	163.19	***	4.44	62.66	***
Topography position (P)	2	231.70	94.97	***	2.87	40.48	***
Soil depth (D)	3	1620.40	664.04	***	15.84	223.58	***
L × T	4	41.90	17.15	***	0.28	3.99	***
L × P	2	120.60	49.42	***	0.17	9.66	0.09
L × D	6	126.00	51.64	***	0.69	9.95	***
T × P	8	43.30	17.76	***	0.71	2.36	***
T × D	12	138.10	56.59	***	0.32	4.52	***
P × D	6	42.80	17.53	***	0.42	5.95	***
L × T × P	7	18.50	7.58	***	0.12	1.63	0.13
L × T × D	12	13.70	5.61	***	0.18	2.55	***
L × P × D	6	84.10	34.46	***	0.44	6.27	***
T × P × D	24	11.20	4.61	***	0.10	1.34	0.14
L × T × P × D	21	23.10	9.47	***	0.11	1.59	0.05
Error	288	2.40			0.07		

df: degree of freedom (*n*-1), MSE: Mean sum of squares, ** values are significant at 0.05, *** values are significant at 0.001

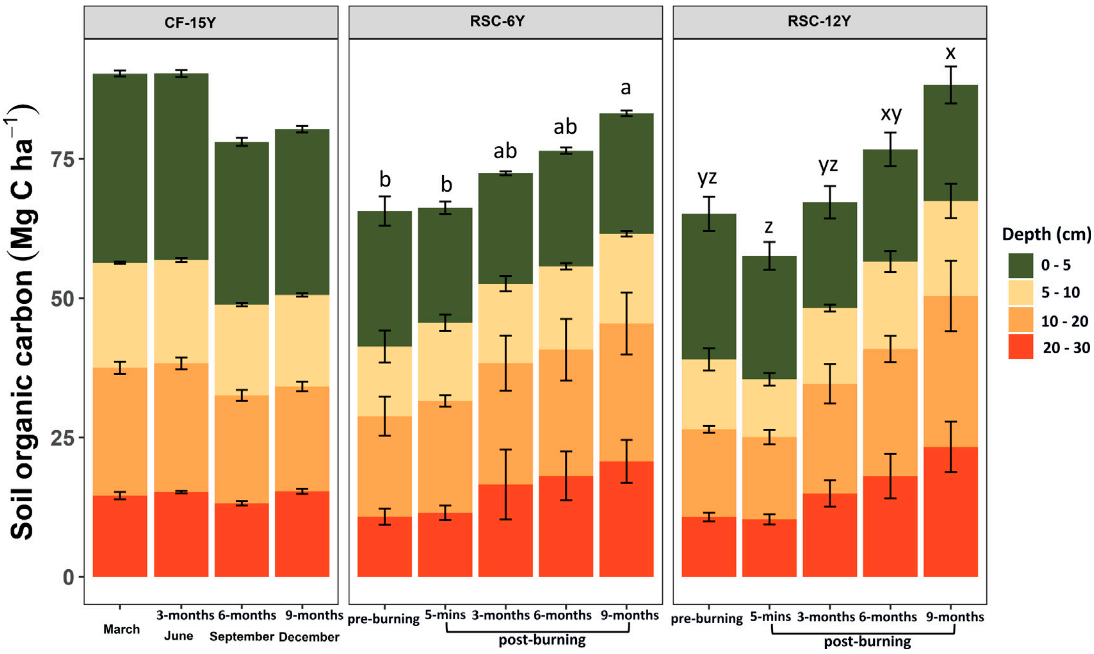

FIGURE 2
Soil organic carbon (Mg C ha^{-1}) of 0–5, 5–10, 10–20, and 20–30 cm soil depth during pre-burning, and different time post-burning: 5-min, 3-month, 6-month, and 9-month under 6-year and 12-year left fallow for all slope positions compared with continues fallow 15-year. a–b and x–z denote significant differences among time period of each field ($p \leq 0.05$).

TABLE 4 Average soil organic carbon (Mg C ha^{-1}) of sample soil: CF-15Y, RSC-12Y and RSC-6Y fields with different left fallow period (year) of RSC, position, soil depth, and chronological time of burning

RSC field		Soil depth (cm)	Time period				
			pre-burning	5- minutes	3-months	6- months	9- months
CF-15Y		0-5	33.90	-	33.45	29.21	29.74
		5-10	18.87	-	18.54	16.28	16.44
		10-20	22.96^{a}	-	23.12^{a}	19.35^{b}	18.77^{b}
		20-30	14.55	-	15.19	13.19	15.36
		Total	90.27^{Aa}	-	90.30^{Aa}	78.03^{Ab}	80.31^{Ab}
RSC-12Y	Upper slope	0-5	22.51^{a}	20.27^{a}	15.16^{b}	16.16^{b}	16.79^{b}
		5-10	15.21	15.04	12.89	14.57	14.84
		10-20	15.67^{a}	15.80^{a}	24.07^{b}	24.75^{b}	25.58^{b}
		20-30	10.57^{a}	10.44^{a}	17.77^{b}	23.30^{c}	24.64^{c}
		Total	63.96^{Ba}	61.55^{Aa}	69.88^{Eb}	78.78^{Ab}	81.85^{Ac}
	Middle slope	0-5	28.25^{a}	24.87^{a}	21.43^{b}	21.88^{b}	21.29^{b}
		5-10	10.99^{a}	10.71^{a}	14.11^{b}	14.30^{b}	15.18^{b}
		10-20	15.15^{a}	14.75^{a}	16.18^{a}	19.89^{b}	21.28^{b}
		20-30	10.07^{a}	9.99^{a}	12.47^{ab}	14.66^{b}	17.57^{b}
		Total	64.45^{Ba}	60.32^{Aa}	64.19^{Ca}	70.74^{Bb}	75.32^{Bb}
	Lower slope	0-5	27.57^{a}	22.20^{b}	20.26^{b}	22.39^{b}	24.38^{b}
		5-10	11.43^{a}	11.36^{a}	13.74^{a}	18.12^{b}	21.15^{b}
		10-20	16.39^{a}	16.29^{a}	18.80^{a}	23.83^{b}	34.28^{c}
		20-30	11.53^{a}	11.43^{a}	14.66^{ab}	16.21^{b}	27.73^{c}
		Total	66.92^{Ca}	61.27^{Ab}	67.47^{Bc}	80.55^{Cd}	107.54^{Ce}
RSC-6Y	Upper slope	0-5	22.33	19.37	20.17	21.42	22.17
		5-10	8.99^{a}	8.95^{a}	15.21^{b}	15.49^{b}	15.61^{b}
		10-20	13.51^{a}	13.37^{a}	16.43^{b}	17.09^{bc}	19.65^{c}
		20-30	9.35^{a}	9.46^{a}	9.77^{a}	14.89^{b}	18.40^{c}
		Total	54.18^{Da}	51.15^{Ba}	61.57^{Db}	68.88^{Dc}	75.83^{Bd}
	Middle slope	0-5	23.14^{a}	19.80^{b}	19.62^{b}	20.44^{a}	21.05^{a}
		5-10	12.93^{a}	12.74^{a}	15.08^{b}	14.94^{ab}	16.58^{b}
		10-20	19.22	19.22	21.12	21.27	22.61
		20-30	12.56^{a}	12.59^{a}	15.89^{ab}	15.53^{ab}	17.95^{b}
		Total	67.85^{Ca}	64.34^{Ca}	71.71^{Eb}	72.18^{Bb}	78.18^{Dc}
	Lower slope	0-5	27.50^{a}	21.52^{b}	19.72^{b}	20.35^{b}	21.65^{b}
		5-10	15.57	15.31	12.46	14.49	16.12
		10-20	21.33^{a}	20.90^{a}	27.68^{b}	29.56^{b}	31.90^{b}
		20-30	10.47^{a}	10.39^{a}	24.10^{b}	23.90^{b}	25.81^{b}
		Total	74.88^{Ea}	68.12^{Db}	83.95^{Fc}	88.30^{Ed}	95.48^{Ee}

$^{A-F}$ denotes significant differences among fields and positions ($p \leq 0.05$), a-c indicates significant differences among time period of each field ($p \leq 0.05$), analyzed by post-hoc Tukey's HSD

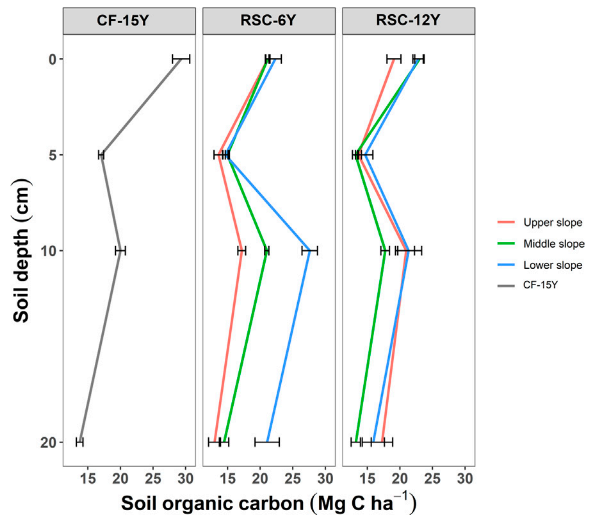

FIGURE 3
Variation of soil organic carbon (Mg C ha^{-1}) with soil depth in different area position under 6-year and 12-year left fallow compared with continues fallow 15-year.

The vertical distribution of SOC and STN stocks is important aspect of soil health and productivity (Figure 3, Figure 5). In CF-15Y, the highest SOC values were observed in March and at the 3-, 6-, and 9-month post-burning stages, specifically within the 0–5 cm depth, with corresponding values of 33.90, 33.45, 29.21, and 29.74 Mg C ha^{-1}. Similarly, SOC was also the highest in RSC-6Y and RSC-12Y fields. It is noteworthy that SOC was higher at the pre-burning stage compared to the post-burning stages in RSC-6Y and RSC-12Y soils (Table 4). At the depth of 10–20 cm in RSC-6Y and RSC-12Y fields, SOC stocks were significantly higher in the lower slope than the surface layer (Figure 3). The STN stock in CF-15Y significantly increased at 9 months post-burning, particularly at a soil depth of 10–30 cm. Although STN stocks in the RSC-6Y site slightly increased at a soil depth of 10–30 cm at 3 and 6 months after burning, STN stock significantly declined at 9 months after the fire for all soil depths. At deeper layers (10–30 cm) of the upper slope, higher STN stocks were observed compared to the middle and lower slope positions. Moreover, the RSC-12Y field exhibited its highest STN stock at a soil depth of 10–20 cm, both in the upper and lower slope positions (Figure 5; Table 5).

3.4 Multivariable analysis

Redundancy analysis revealed that there were varying relationships between SOC and STN and soil properties in different topographic positions (Figures 6A,B). In Figure 6A, the RDA plot explains 51.88% of the variation in the position of RSC-6Y (adj. R^2 = 0.48). Three topographic positions were separated along the first axis, with middle and upper slope areas (21.2%) separated from the lower slope area, while the second axis separated the middle slope area (30.6%) from the other two positions. Figure 6A clearly illustrates the significant impact of slope position on the SOC in the RSC-6Y site. The

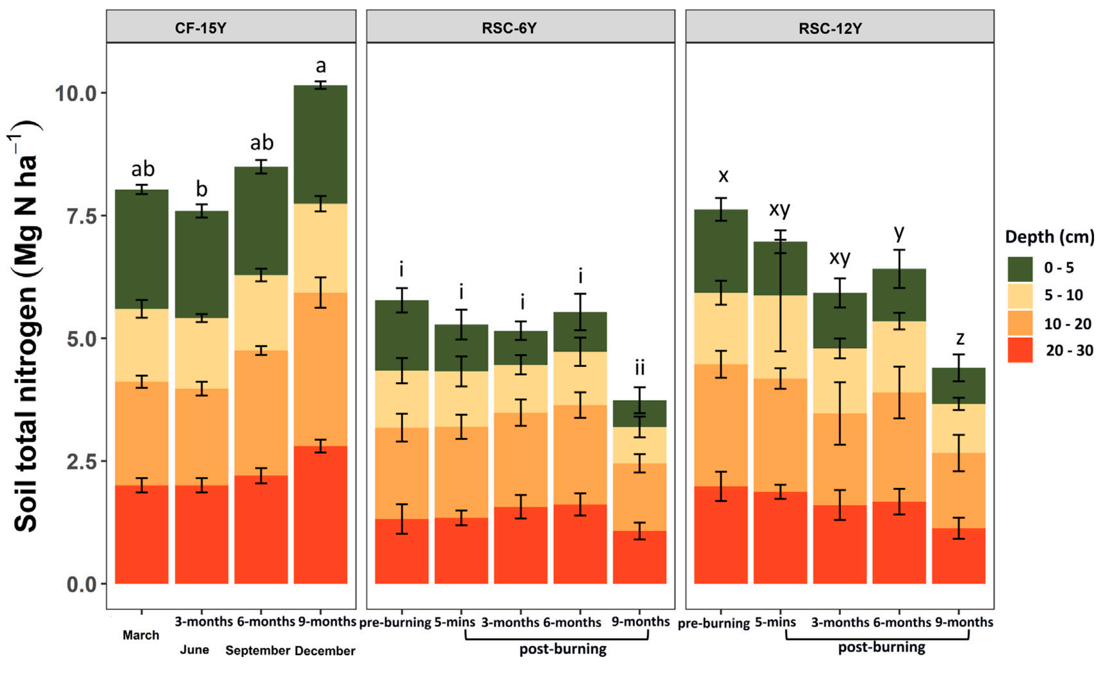

FIGURE 4
Soil total nitrogen (Mg N ha^{-1}) of 0–5, 5–10, 10–20, and 20–30 cm soil depth during pre-burning, and different time post-burning: 5-min, 3-month, 6-month, and 9-month under 6-year and 12-year left fallow for all slope positions compared with continues fallow 15-year. a–b, i–ii, and x–z denote significant differences among time period of each field ($p \le 0.05$).

TABLE 5 Average soil total nitrogen (Mg N ha^{-1}) of sample soil: CF-15Y, RSC-12Y and RSC-6Y fields with different left fallow period (year) of RSC, position, soil depth, and chronological time of burning

RSC field		Soil depth (cm)	Time period				
			pre-burning	5- minutes	3-months	6- months	9- months
CF-15Y		0-5	2.43	-	2.18	2.20	2.41
		5-10	1.48^{a}	-	1.44^{a}	1.54^{a}	1.81^{b}
		10-20	2.11^{a}	-	1.97^{a}	2.55^{b}	3.12^{c}
		20-30	2.01^{a}	-	2.01^{a}	2.20^{a}	2.81^{b}
		Total	8.03^{Aa}	-	7.59^{Aa}	8.49^{Aa}	10.16^{Ab}
RSC-12Y	Upper slope	0-5	1.61^{a}	1.20^{a}	1.06^{ab}	0.89^{b}	0.62^{b}
		5-10	1.41	1.32	1.35	1.46	0.99
		10-20	2.75^{a}	2.75^{a}	2.03^{ab}	2.48^{a}	1.72^{b}
		20-30	2.30^{a}	2.44^{a}	1.43^{b}	1.63^{b}	1.10^{b}
		Total	8.07^{Aa}	7.71^{Aa}	5.87^{Bb}	6.46^{Ab}	4.43^{Bb}
	Middle slope	0-5	1.51^{a}	1.10^{a}	0.85^{ab}	0.74^{b}	0.51^{b}
		5-10	1.21^{a}	2.43^{b}	1.12^{a}	1.30^{a}	0.90^{a}
		10-20	2.45^{a}	2.40^{a}	1.13^{b}	1.54^{b}	1.05^{b}
		20-30	1.73a	1.82^{a}	1.41^{a}	1.41^{a}	0.92^{b}
		Total	6.90^{Ba}	7.75^{Aa}	4.51^{Bb}	4.99^{Bb}	3.38^{Bb}
	Lower slope	0-5	1.98^{a}	1.33^{b}	1.49^{ab}	1.56^{ab}	1.08^{b}
		5-10	1.74^{a}	1.57^{a}	1.50^{a}	1.60^{a}	1.11^{b}
		10-20	2.25^{a}	2.39^{a}	2.43^{ab}	2.65^{b}	1.82^{a}
		20-30	1.93^{a}	1.98^{a}	1.98^{a}	1.98^{a}	1.38^{b}
		Total	7.91^{Aa}	7.26^{Aa}	7.40^{Aa}	7.79^{Aa}	5.40^{Bb}
RSC-6Y	Upper slope	0-5	1.34^{a}	0.86^{a}	0.62^{b}	0.69^{b}	0.46^{b}
		5-10	1.11	1.07	0.97	1.16	0.79
		10-20	2.14^{a}	2.14^{a}	2.14^{a}	2.22^{a}	1.55^{b}
		20-30	1.64^{ab}	1.83^{a}	1.83^{a}	1.88^{a}	1.27^{b}
		Total	6.22^{Ba}	5.89^{Bab}	5.56^{Bab}	5.96^{Bb}	4.07^{Bb}
	Middle slope	0-5	1.23^{a}	0.68^{ab}	0.54^{b}	0.45^{b}	0.30^{b}
		5-10	0.91^{a}	0.86^{a}	0.76^{a}	0.73^{a}	0.48^{b}
		10-20	1.81^{a}	1.95^{a}	1.91^{a}	1.90^{a}	1.26^{b}
		20-30	1.06^{a}	1.39^{a}	1.44^{ab}	1.53^{b}	1.01^{a}
		Total	5.00^{Ba}	4.88^{Ba}	4.64^{Ba}	4.62^{Ba}	3.05^{Bb}
	Lower slope	0-5	1.73^{a}	1.23^{b}	0.91^{b}	1.27^{ab}	0.88^{b}
		5-10	1.47^{a}	1.40^{a}	1.19^{a}	1.37^{a}	0.94^{b}
		10-20	1.63^{a}	1.75^{a}	1.71^{a}	1.95^{a}	1.34^{b}
		20-30	1.27^{a}	1.30^{a}	1.44^{a}	1.44^{a}	0.94^{b}
		Total	6.10^{Ba}	5.68^{Ba}	5.26^{Ba}	6.03^{Ba}	4.10^{Bb}

$^{A-F}$ denotes significant differences among fields and positions ($p \leq 0.05$), a-c indicates significant differences among time period of each field ($p \leq 0.05$), analyzed by post-hoc Tukey's HSD

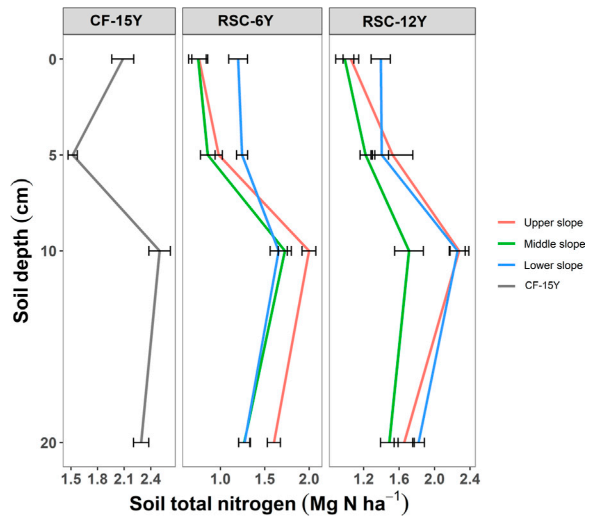

FIGURE 5
Variation of soil total nitrogen (Mg N ha-1) with soil depth in different area position under 6-year and 12-year left fallow compared with continues fallow 15-year.

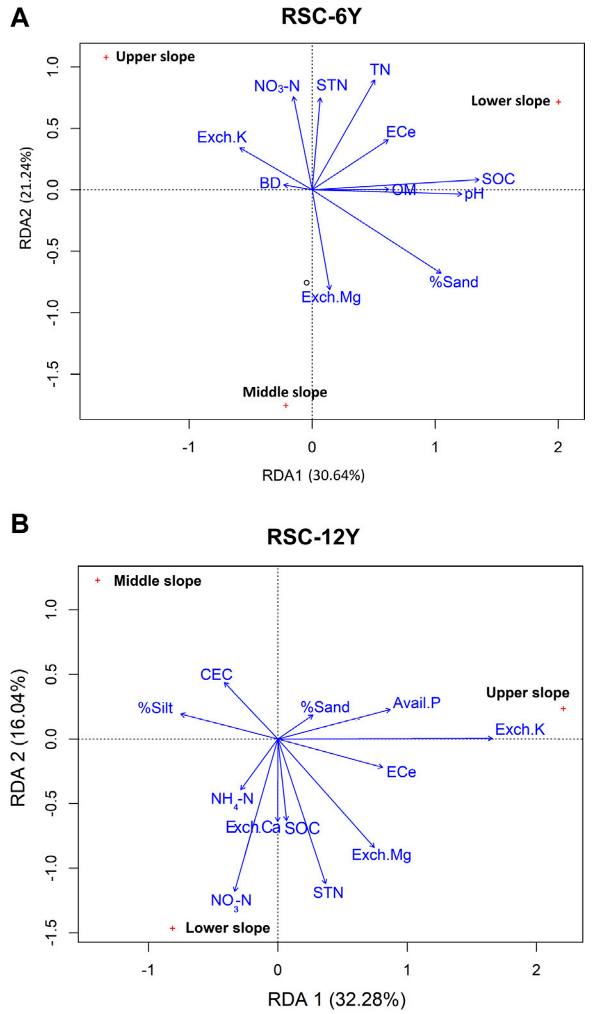

FIGURE 6
Redundancy analysis (RDA) of soil samples (0–30 cm) using soil properties response variables and quantitative explanatory variables under **(A)** 6-year left fallow and **(B)** 12-year left fallow in different position: lower, middle, and upper slopes.

results demonstrate that SOC is highly influenced by the lower slope position, while the upper slope position exhibits an opposite effect. The following factors have a similar trend as SOC: pH and OM, while sand content and ECe have a less pronounced effect. On the other hand, bulk density and exch. K exhibit an opposing trend to SOC across the different slope positions. Meanwhile, nitrogen compounds (STN, NO_3-N and TN) were closly associated with both upper and lower slope position.

For the RSC-12Y, the RDA plot used two axes to explain 48.32% of the variation in the three topographic positions (adj.R^2 = 0.45, as shown in Figure 6B). The results indicate that NO_3-N, STN, SOC, exch. Ca, and NH_4-N were highly influenced by the lower slope position. On the other hand, Exch. K, Avail. P, sand content, and ECe were positively associated with the upper slope, while silt content and CEC were associated with the middle slope.

3.5 Soil surface loss

In the RSC-6Y, noticeable soil surface loss occurred in the middle and upper slopes 9 months after burning, even though the losses in these two slopes at the same post-burning stage did not display significant differences. In the RSC-12Y, the highest amount of soil surface loss was observed in the upper slope at the 9-month post-burning stage, totaling 4.98 cm lost. Notably, soil surface loss in the same fallow was significantly lower in the lower slope at all post-burning stages. In CF-15Y, a slight soil surface gain of 0.6 cm was noted in June, whereas this fallow experienced soil surface losses of 1.0 cm in September and 1.8 cm in December (Figure 7).

4 Discussion

4.1 Effect of fallow periods on soil properties and soil surface loss

The results indicate that the CF-15Y had the highest OM and SOC stocks, particularly in the surface layer (0–5 cm) (Figure 2, Figure 3; Table 4). This trend was also observed for STN stocks (Figure 4, Figure 5; Table 5). Older fallow fields accumulate more leaf litter and other organic debris from above and below-ground biomass (Murovhi et al., 2012). In addition, the roots of weeds and grasses are a significant source of OM in the surface layer (Arunrat et al., 2023). This finding is consistent with Sharma et al. (2022), who reported that higher OM inputs from persistent vegetation cover in older fallow fields contribute to the higher OC content compared to

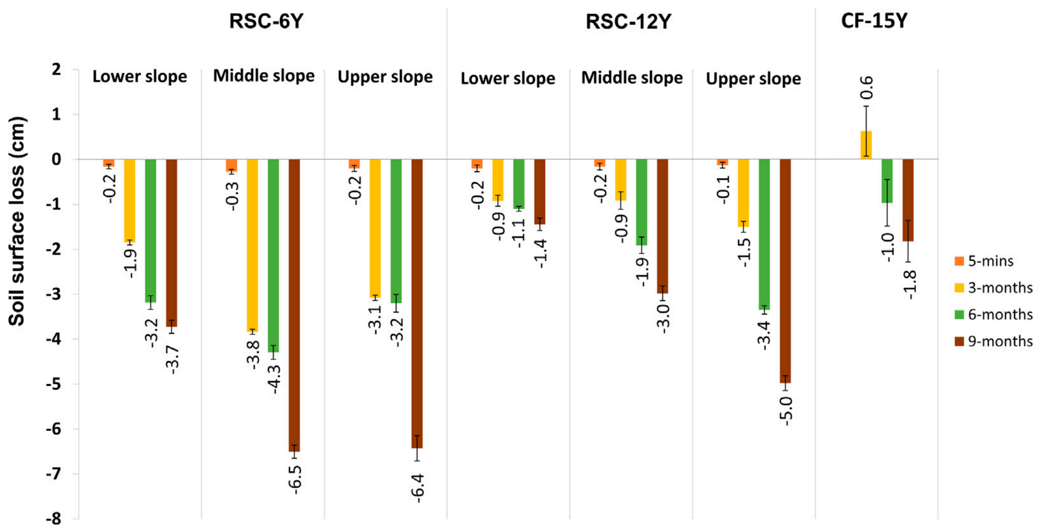

FIGURE 7
Soil surface loss (cm) of lower, middle, and upper slope during different time post-burning: 5-min, 3-month, 6-month, and 9-month under 6-year and 12-year left fallow compared with continues fallow 15-year.

younger fallow fields. The lower soil pH in CF-15Y compared to RSC-6Y and RSC-12Y (Table 3) suggests that it is rich in OM and undergoes more organic acid production during decomposition processes, which is consistent with Hong et al. (2019).

Currently, the fallow period of RSC fields has shortened due to population pressures and forest laws and regulations. As a result, most of the long-term fallow fields (>10 years) have become secondary natural forests, making it difficult to identify evidence of their previous boundaries. Thus, those fields eventually were no longer RSC fields; instead, they became natural forests. The shorter fallow cycle diminishes the ability of RSC to recover the ecosystem due to the loss of soil fertility through runoff and leaching, as observed in the current study (Figure 6). Prokop and Poreba (2012) found that 32–79 Mg ha^{-1} $year^{-1}$ of soils were lost in the short fallow period of root crop cultivation on steep slopes in Northeast India. On the other hand, the loss of soil under natural forest was reported to range from 0.04 to 0.52 t ha^{-1} $year^{-1}$ in Meghalaya, India (Saha et al., 2011). Arunrat et al. (2022b) found that the average soil erodibility at the topsoil (0–30 cm) of natural forest in northern Thailand was 0.1337 t h MJ^{-1} mm^{-1}, the lowest value compared to crop lands. It takes several years for the restoration of topsoil nutrients after the conversion of natural forest to cropland. In northern Vietnam, Dung et al. (2008) estimated that the recovery of nitrogen and phosphorus would require more than 30 years and more than 6 years, respectively. In northern Thailand, Arunrat et al. (2023) observed that SOC and STN stocks had not reached pre-fire levels even after 2 years had passed. Meanwhile, a longer cycle duration allowed the germination of weed seeds and regrowth, which enhances the recovery of soil nutrients and reduces soil loss (Figure 7). Yadav (2013) found that the losses of carbon and nutrients in older fallow fields did not significantly affect crop productivity compared to younger fallow fields. Nevertheless, the findings of our current study, as depicted in Figure 7, demonstrate that CF-15Y experienced soil loss during the rainy season, with soil surface losses ranging from 1.0 to 1.8 cm. This phenomenon could be attributed to the substantial rainfall and resultant runoff, which likely led to soil deposition at the lowest slope position.

4.2 Effect of fire on soil properties and soil surface loss

The effects of fire on soil are primarily confined to the upper 10 cm of soil, where it can reduce soil moisture and increase soil temperature (Supplementary Table S1). This is because the increase in soil temperature can be attributed to the removal of canopy cover, loss of OM insulation, and deposition of black ash on the soil surface caused by the fire, which subsequently led to higher rates of evaporation (Cooperdock et al., 2020). The different heating temperatures during the fire altered the color of the ash, resulting in dark, reddish-brown ash that contained higher levels of pH, organic matter, electrical conductivity, total nitrogen, and soil nutrients (except available calcium) when compared to gray and white ashes (Supplementary Table S2). Black ash, which is the product of incomplete combustion of the litter containing a high proportion of carbon, is typically produced at low temperatures (<300 °C) (Úbeda et al., 2009). The reddish color of ash is due to the oxidation of iron minerals at low temperatures (Markl et al., 2006), while gray or white ash indicates high fire severity and more complete combustion of litter, which occurs at temperatures above 500 °C (Kuzyakov et al., 2018).

There is significant concern that shifting cultivation practices could deplete soil carbon and consequently increase CO_2 levels in the atmosphere (Bruce et al., 1999). Detwiler (1986) estimated that shifting cultivation could lead to an average loss of 40% of soil carbon within 5 years. The current study found similar results to previous research, which showed a decline in SOC stocks in the surface layer (0–5 cm) at both RSC-6Y and RSC-12Y sites (as shown in Figure 2, Figure 3). This decline can be attributed to the combustion of OM in the soil, which is released into the atmosphere as CO_2. The decline in STN stock after a fire (Figure 4, Figure 5) is attributed to the oxidation of OM through oxidized nitrogen gases and dinitrogen (N_2) (Saplalrinliana et al., 2016). The decline in STN stocks continued even 9 months after burning in both RSC-6Y and RSC-12Y sites, as shown in Figure 4, Figure 5. This could be attributed to soil leaching and erosion caused by heavy rainfall, as the soil was left uncovered after burning. According to Bechmann (2014), nitrogen is highly susceptible to loss through surface and subsurface runoff in sloped areas. This can result in nutrient depletion and subsequently lead to reduced plant growth and productivity. Soil pH and ECe can increase after burning due to the release of basic cations (such as calcium, magnesium, and potassium) and the accumulation of ash, which contains alkaline materials (Table 1). The post-fire increase in ECe can also be attributed to the leaching of salts from the ash and the subsequent increased availability of nutrients that contribute to ion exchange processes in the soil (Da Silva Neto et al., 2019). The combustion of OM during a fire can release soil nutrients, such as Avail. P, Exch. K, Exch. Ca, Exch. Mg, and NH_4-N, which could explain their increase after burning (Table 2). The increase in soil nutrients can be attributed to the ash generated from the combustion of vegetation, which contains essential nutrients that can replenish the soil (Saplalrinliana et al., 2016).

The loss of soil surface in RSC areas is a major concern not only for the loss of sediment but also for the decline in soil nutrients, as evidenced in the current study (Figure 7; Table 2). The burning of vegetation by fire strips away its protective cover, leaving the soil susceptible to erosion by wind and water. In addition, the heat generated by the fire can induce soil hydrophobicity, making it more prone to water repellency and erosion. Further, soil OM and structure loss due to burning can make the soil more vulnerable to erosion and result in a decline in soil nutrient availability. Our findings are also consistent with the study by Dass et al. (2010) who reported that soil nutrient losses of N, P, and K were primarily due to runoff and erosion in southern Orissa, India. Following the 3-month period post-burning, a discernible trend of rising SOC stocks was observed, persisting through the upland rice harvest stage at 9 months after burning, as depicted in Figure 2 and detailed in Table 1 (refer to OC values). The ash and charcoal left after burning can act as a source of nutrients and OM, leading to increased SOC levels. Chatterjee et al. (2022) reported an increase in SOC in shifting cultivation systems in India during the crop growing and fallow stages, which was attributed to the addition of OM from the regrowth of vegetation. Weeds and grasses can help to restore soil fertility during the fallowing phase (Xiao et al., 2022).

4.3 Vertical distribution and slope effect on soil properties and soil surface loss

The properties of soil can differ according to the depth in the soil profile, primarily attributed to the accumulation of OM, changes in soil texture and structure, and climate. Moreover, the topography of the land can also play a significant role in soil properties and surface loss, impacting factors such as soil erosion and nutrient availability. In RSC-6Y, an increase in SOC stock was observed at deeper layers (5–10 cm) after burning, resulting in higher levels than those before burning. At a depth of 10–30 cm, SOC stocks were significantly higher at lower slopes compared to the surface layer (Figure 3). There are two possible reasons for the increase in SOC and STN in deeper layer after a fire: ash deposition and vegetation changes. During a fire, OM is burned, and carbon is released into the atmosphere as CO_2. However, some carbon remains in the form of charcoal or ash, which contains high levels of carbon and other plant nutrients, such as Ca, Mg, and K. When deposited in the soil, ash can be incorporated into deeper layers over time through erosion, bioturbation, or leaching (Bodí et al., 2014). After a fire, some plant species may be replaced by others with higher root biomass. These new plants can add OM to the soil through litterfall and root exudates, contributing to an increase in SOC and STN. They may also allocate more carbon to belowground biomass, such as roots, resulting in an increase in SOC and STN in deeper soil layers (Deng and Shangguan, 2017; Gross and Harrison, 2019). Sheikh et al. (2009) reported that the decline in SOC and STN with increasing soil depth could be attributed to the decomposition of plant residues, which were primarily located on the soil surface. The occurrence of heavy rainfall can lead to a decline in soil nutrients from the topsoil to the subsoil layer due to leaching losses, which can in turn promote the rapid growth of invasive weeds, as observed in the study conducted by Wapongnungsang et al. (2019).

Soil surface loss after a fire in sloped areas can have significant impacts on soil physicochemical properties (Figure 6). These impacts can be far-reaching and have long-term consequences for the growth and productivity of plants, as well as for the health and functioning of ecosystem. In sloped areas, the upper slope generally experiences greater erosion rates and soil surface loss compared to the lower slope or foothill areas. This is because the upper slope is more exposed to erosive forces such as rainfall and surface runoff, and the steeper gradient of the slope increases the velocity of water flowing over the soil surface. As a result, the upper slope tends to have thinner topsoil and lower OM and TN contents compared to the lower slope or foothill areas. The study conducted by Neergaard et al. (2008) supports the current study, as it revealed that the soil base-forming cations (K, Ca, Mg, and Na) and ECe exhibited significantly higher values in downslope soils when compared to upslope soils. Another possible mechanism, as explained by Bruun et al. (2006), is the loss of ash from the upper slope towards the foot of the slope. Gafur et al. (2003) also found that soil nutrients were washed away from the upper 10 cm and accumulated as sediments in the lower slope of shifting cultivation. Li et al. (2019) reported that depositional profiles at subsoil depth had significantly higher levels of SOC compared to non-eroding or eroding profiles, indicating greater SOC storage in those profiles. Furthermore, the slope can affect the rates of water infiltration and runoff. As the slope increases, the larger surface area and faster water flow lead to a decrease in infiltration. This results in a reduction of soil moisture content in deeper layers due to increased runoff and evaporation rates (Florinsky, 2012). However, future research could explore the vertical distribution and slope effects on soil properties and soil surface loss in RSC. This includes investigating the long-term effects of land use changes on soil properties, elucidating the physical and chemical processes contributing to soil erosion, and understanding how these processes vary across different slopes and soil types, as well as the effects of soil microbial communities. Such research efforts can provide a better understanding of the relationships between slope, depth, soil properties, and erosion rates, and inform sustainable land use and management practices that promote soil health and productivity.

5 Conclusion

Our study found that the SOC stock increased at 6- and 9-month post-burning, which were higher than the pre-burning levels. At deeper layers (5–10 cm), there was an upward trend in SOC stock resulting in higher values than pre-burning levels. The depth of 10–20 cm showed an increase in SOC stocks at lower slopes and higher than the surface layer. In contrast, STN stock decreased at the surface soil post-fire, while it increased in deeper layers at all slope positions. During the rainy season (September), the highest soil surface losses were observed after the fire, with the greatest losses occurring at the upper slope and the lowest at the lower slope. Additionally, lower slopes were found to be closely associated with SOC, STN, ECe, NO_3-N, NH_4-N, Exch. Ca, and Exch. Mg. To mitigate the negative effects on soil properties after fire, it is crucial to explore and implement effective post-fire management strategies.

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

NA: conceptualization, methodology, investigation, writing—original draft, and writing—review and editing. SS: conceptualization, methodology, investigation, and writing—original draft. PK: methodology, investigation, and writing—original draft. MY: supervision. RH: conceptualization, methodology, and supervision.

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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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Jurisdictional approaches to High Conservation Value area designation using regulatory instruments: an Indonesian pilot project

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Agricultural expansion is the primary driver of tropical deforestation and ecological degradation. Certification schemes for sustainable agricultural supply chains, such that of the Roundtable on Sustainable Palm Oil (RSPO), seek to address this issue by identifying and protecting High Conservation Value (HCV) areas within concessions. Although RSPO certification of individual concessions has been beneficial, it has had limited efficacy in arresting systemic ecological degradation at larger scales. In response, certification at a regional, 'jurisdictional' scale concordant with local environmental regulation has been proposed as an alternative to conventional, piecemeal certification. Jurisdictional certification schemes require alignment with local legislation to ensure integration with governmental environmental and land-use planning; yet, questions of which legislation, and at which level of government, have remained unaddressed. Here, we report on a pilot jurisdictional RSPO certification scheme implemented by an Indonesian district, based on environmental carrying capacity assessments (ECCA) as legislated by the district government. Using the ECCA, we identified likely HCV areas across the district and considered their distributions with respect to three factors of feasible HCV management: (a) similarity with alternative HCV areas identified by a conventional HCV Screening method, (b) sensitivity to aspects of underlying legislation, and (c) scope for unilateral district-wide management. Likely HCV areas were generally similar between the ECCA and HCV Screening method, as each set spanned ~90% of the district. However, higher-confidence HCV areas according to the ECCA were much less extensive, at 51% of the district, and uniquely extensive across oil-palm concessions. HCV area designation was highly sensitive to the legislated parameters of the ECCA, namely, the selection and estimation of key ecosystem services. Potentially, subtle variations to ECCA implementation, such as those proposed by agro-industrial lobbyists, would significantly affect jurisdictional HCV designations. Finally, some three-quarters of all HCV areas and higher-confidence HCV areas designated by the ECCA fell outside of the exclusive administrative authority of the district government, being confined to agricultural zones. In politically-decentralised Indonesia, jurisdictional

HCV area management would therefore be narrowly confined to agricultural areas, or cooperation between district, provincial, and central governments would be essential to the protection of HCV areas generally across districts.

KEYWORDS

environmental assessment, HCV screening, sustainable oil palm, jurisdiction, ecosystem service

1 Introduction

Tropical biodiversity is besieged by many threats, including the over-exploitation of forests (Maxwell et al., 2016), hunting (Tilker et al., 2019), pollution (Hölker et al., 2010), fire (Kelly et al., 2020), climate change (Sintayehu, 2018), invasive species (Doherty et al., 2016), and habitat destruction (Hanski, 2011). In recent decades, increased global demand for agricultural and forest commodities has driven most tropical deforestation and ecological degradation (Gibbs et al., 2010; Hosonuma et al., 2012; Sloan and Sayer, 2015; Austin et al., 2017a; Austin et al., 2017b). In Indonesia, host to two global biodiversity hotspots (Sloan et al., 2014), the main drivers of deforestation since the early 2000s are the development of industrial-scale concessions for pulp and paper, timber, and especially oil-palm plantations (Carlson et al., 2013; Gaveau et al., 2014; Gaveau et al., 2016; Gaveau et al., 2022; Abood et al., 2015). This deforestation has had detrimental effects for ecosystem service provision, such as fire mitigation (Nikonovas et al., 2020), biodiversity (Sodhi et al., 2004; Edwards et al., 2010; Corlett, 2014), and water regulation (Casagrande et al., 2021).

Commodity-driven deforestation and environmental degradation in Indonesia has led to civil-society campaigns, such as global consumer boycotts, which have affected policies in countries importing Indonesian timber, palm oil, and other commodities (Lambin et al., 2018). For instance, in 2016 the European Union adopted the Forest Law Enforcement, Governance and Trade (FLEGT) regulations to exclusively import Indonesian timber that is certified as legally sourced (Tacconi, 2007; van Heeswijk and Turnhout, 2013). Commodity producers, in turn, have responded to such economic and regulatory pressures via various sustainable-production initiatives, such as corporate zero-deforestation pledges (Furumo and Lambin, 2020; Carodenuto and Buluran, 2021), fire-free production schemes (Carbon Conservation, 2017; Watts et al., 2019; Sloan et al., 2021), and commodity supply-chain certification schemes (Kadarusman and Herabadi, 2018). Supply-chain certification schemes, including the well-known Forest Stewardship Council (FSC) and the Roundtable on Sustainable Palm Oil (RSPO), entail the identification and protection of High Conservation Value (HCV) areas within otherwise productive concessions to avoid their unsustainable conversion. HCV areas are variously defined as host to high biodiversity, rare species and/or critical habitats, and/or as providing significant ecosystem services, and/or as having high socio-cultural importance to local communities (Edwards et al., 2011; Austin, et al., 2017).

The RSPO's Principles and Criteria guide member oil-palm growers in producing certifiable sustainable palm-oil production (RSPO, 2021a), including stipulating the identification and protection of HCV areas (e.g., Principle 7) (RSPO, 2018). Amongst various considerations covered by these Principles and Criteria, RSPO certification requires that HCV areas be identified by accredited third-party environmental consultants, both in existing concessions and those to be established. Thereafter, the individual concessionaire is charged with the monitoring and protection of its HCV areas in order to retain its RSPO certification. To date, the RSPO Principles and Criteria have been applied in 92 countries, including Indonesia, by far the world's foremost oil-palm producer (Statista Research Department, 2022). While current RSPO-certification practices have ostensibly lowered overall deforestation, they have proven less effective at reducing generalized ecological degradation, as with respect to biodiversity loss, burning, and peatland conversion (Ruysschaert and Salles, 2014; Azhar et al., 2015; Carlson et al., 2017; Morgans et al., 2018; Scriven et al., 2019). Amongst other shortcomings, RSPO Principles and Criteria implementation has been highly piecemeal. HCV areas have been identified at the level of individual concessions, culminating in ecologically and administratively disjointed conservation planning across the multiple concessions and forested areas within a given region (Runting et al., 2015; Sloan et al., 2019). More geographically and ecologically holistic approaches to HCV-area designation are necessary.

In response, the RSPO launched a new certification initiative in 2018, known as the Jurisdictional Approach (JA) (RSPO, 2021b). The JA seeks to scale the application of RSPO Principles and Criteria from the concession to a regional, 'jurisdictional' scale. In theory, the JA would entail a single designation of HCV areas across a given administrative jurisdiction[1], allowing for greater coordination amongst concessionaires and local governmental environmental regulators with respect to RSPO certification standards. Theoretical advantages of the JA include a greater total extent of Principles and Criteria implementation; regulatory support of market forces for sustainability; increased market access for producers by virtue of their 'collective certification' (Watts and Irawan, 2018), and economies of scale for financial and administrative aspects of HCV designation and RSPO compliance generally, particularly amongst smaller producers (RSPO 2021).

The JA to RSPO certification arguably necessitates that HCV designations are based on, or otherwise compatible with, local regulatory instruments. Thus, local governments would realise jurisdictional HCV designations or otherwise integrate them

1 According to RSPO (2021b, p. 8), a jurisdiction is defined as "a government administrative area where a system of laws is applied, it could mean a country, a state, a province, or a district, led by an authority that has the power or right to govern and to interpret and apply the law. Jurisdictions operate according to a set of regulations, which define the mandates and authorities in planning, budgeting and implementation of programmes and activities".

seamlessly with official land-use planning. This practicable aspect of the RSPO JA has been largely neglected to date. Indeed, recent guidelines for jurisdictional HCV Screening issued by the High Conservation Value Network (Watson, 2020) would effectively 'scale up' conventional RSPO HCV-assessment methods intended for concession-level application. While HCV Screening is potentially beneficial as an input to jurisdictional land-use planning, no means of integrating HCV Screening with Indonesian environmental planning are immediately apparent.

An alternative approach to jurisdictional HCV-area designation is to adapt existing environmental regulatory instruments to identify and protect HCV areas. Questions of which instrument, and at which administrative scale, have remain entirely unaddressed. In Indonesia, the jurisdiction with the authority to regulate agricultural commodity production is typically the district (*kabupaten*) (Irawan et al., 2019; Seymour et al., 2020). Amongst Indonesian districts, one regulatory instrument amenable to the JA is the Environmental Carrying Capacity Assessment (ECCA). Since 2009, Indonesian law[2] on Environmental Protection and Management requires all district and provincial authorities to undertake a detailed, spatially-explicitly, wall-to wall ECCA to ensure that planned socio-economic development (including agricultural expansion) will not adversely impact the provision of key ecosystem services (Watts and Irawan, 2018). Local governments must incorporate ECCA outputs into their environmental protection and management plans, medium-term development plans, and land-use/development plans to avoid or mitigate the negative ecological effects of development. To date, no more than 20% of district and provincial authorities have undertaken ECCAs.

Here, for an Indonesian district piloting a JA to RSPO certification, we explore how, and how well, its ECCA may identify likely HCV areas compared to the conventional HCV Screening method currently advanced for jurisdictional applications. We adapted this district's ECCA to realise a jurisdictional HCV-area designation and then considered the distribution of resultant HCV areas in relation to three factors bearing on the feasibility of jurisdictional HCV-area management, namely, (1) the similarity of resultant HCV areas compared to HCV areas identified by the HCV Screening method, (2) the sensitivity of resultant HCV-area designations to the selection and estimation of ecosystem services as legislated by the ECCA, and (3) the scope for unilateral district-wide management of the HCV areas in the context of Indonesian political decentralization.

2 Materials and methods

2.1 Study area

Seruyan District of southern Central Kalimantan Province, Indonesia (Figure 1) is one of three jurisdictions selected globally for pilot implementation of the RSPO JA, alongside Sabah State, Malaysia and the whole of Ecuador. Encompassing 16,404 km^2, this district spans mostly lowlands, although undulating terrain covered with dense forest also occurs within its northern reaches. The central part of the district is mostly lowland oil-palm plantations on mineral soils, while the southern part is comprised by lowland forest, peat swamp forest, and mangrove, some of which fall within the Tanjung Puting National Park.

Deforestation and forest fragmentation have been expanding in Seruyan District since the early 1990s (Figure 1), mirroring trends for Kalimantan and Indonesia generally (Miettinen et al., 2016; Watts and Irawan, 2018; Watts et al., 2019). Since 1990, and particularly since 2000, after Indonesia's political decentralization, forest in the southern and central parts of the district declined by 4,822 km^2, or approximately 55% of the official Indonesian Forest Estate of the district as of 1990, due to logging and/or subsequent conversion to oil palm (Figure 1) (MoEF, 2019a). The district's forests are home to endangered species including Bornean orangutans, proboscis monkey, clouded leopard, and helmeted hornbill (Matsuda et al., 2009; Manduell et al., 2011; Cheyne et al., 2013), populations of which are scattered in forest fragments for which conservation is increasingly essential for species' viability (Gaston and Fuller, 2008). Biodiversity in Seruyan District is relatively understudied, compared to elsewhere in Kalimantan, which may undermine the scientific basis of potential conservation policies locally. In this context, Seruyan District declared its commitment to pilot the RSPO JA in 2015 and issued supporting regulations to initiate the process in 2016 (Watts and Irawan, 2018; Seymour et al., 2020).

2.2 Methodological overview

In collaboration with the government of Seruyan District, we adapted its recent ECCA for the district as a jurisdictional approach towards the identification of likely HCV areas. We then compared these HCV areas against those identified for the same district using conventional methods of the HCV Screening Method advanced by the HCV Network (Table 1). Additionally, we quantified the degree to which HCV areas according to the ECCA are dependent on particular ecological services surveyed by the ECCA and, therefore, are sensitive to the selection and/or estimation of such ecological services. Finally, we quantified the degree to which HCV areas according to the ECCA span areas under the exclusive authority of the district government versus other administrative levels of Indonesian government.

2.3 Environmental carrying capacity assessment (ECCA)

We worked with the Seruyan District Environmental Agency to conduct a district-wide ECCA following guidelines developed by the Ministry of Environment and Forestry (MoEF, 2019b). Of 18 ecosystem services prescribed by MoEF ECCA guidelines, the district's ECCA ultimately surveyed seven services deemed most relevant to sustainability planning and for which empirical observations were relatively confident, according to the Seruyan District government and following its consultation with the MoEF. The seven ecosystem services are: (i) food provisioning, (ii) water

2 National law 32/2009 on Environmental Protection and Management.

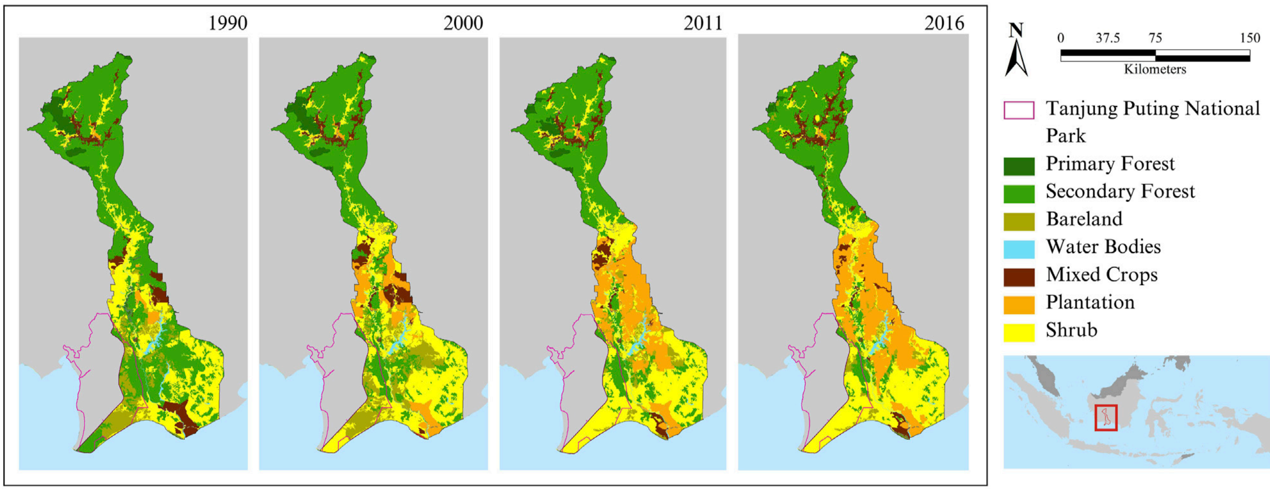

FIGURE 1
Land-use/cover change in Seruyan District, 1990—2016. Source: MoEF (2019a). Notes: Secondary forests according to Ministry of Environment and Forestry refers to any forested area that has been logged.

TABLE 1 A comparison the environmental carrying capacity assessment (ECCA) and HCV Screening method with regard to HCV identification.

	ECCA	HCV screening
Unit/level	Jurisdiction area (i.e., district or provincial administrative area)	Conventional HCV assessments focused on the concession level, while the HCV Screening focuses on a landscape or jurisdiction, to be defined as part of the screening exercise.
User	Government bodies (national and local level)	Government bodies, NGOs, donors, and investors, for example, to meet objectives of spatial planning, jurisdictional certification or supply chain risk management.
Regulation	Compulsory (Act 32/2009 on Environmental protection and management plan)	Voluntary; there is no regulation mandating HCV Screening
Data source	Guidelines and parameters are mostly from the Indonesian Ministry of Environment and Forestry (MoEF), including spatial data (landscape, natural vegetation, land cover). Non-spatial data can come from other sources (e.g., Seruyan District Statistic, expert consultation)	Spatial and non-spatial data, including socio-culture-economic and biodiversity data from disparate global datasets, reports, and publications from government bodies (e.g., MoEF, Geospatial Agency, spatial planning), NGOs, research institutions, and expert consultations.
Spatial resolution	Medium spatial resolution of input data (e.g., SPOT and Landsat satellite sensor processed as 1:250,000 scale); relatively high spatial detail or nuance in HCV-area designation	High to medium resolution of input data; relatively low spatial variation or nuance to HCV-area designations depending on the data available
Implementation	Desktop study, ideally alongside biodiversity survey and ground check	Desktop study—can be combined with targeted field work and consultation
HCV indicators	Indicators of likely HCV area are defined for the jurisdiction as a whole. The selection of ecosystem services for analysis, and the thresholds for their estimation, is guided by official regulation.	Indicators are static, typically presence/absence variables, and selected specifically for each HCV classes (HCV 1—6). Indicators selection reflects analyst judgement and data availability.
Outputs	Delineation of where HCV areas are relatively more or less likely to be present, by ecosystem service	Delineation of where HCV areas are relatively more or less likely to be present, by HCV class; summaries of HCV threats; overlay of HCV likelihood and threats to define 'HCV priority areas'
Post-analysis actions	Incorporate HCV assessment into regional development planning	Discuss screening result implications with stakeholders and determine next steps
Advantage	Regionally holistic; allows for gradations of HCV likelihood; backed by regulation to ensure protection and management at jurisdiction scale	Amenable to a wide range of data sources; flexible criteria for HCV-area designation
Disadvantage	Potential subjectivity in weighing and scoring variables of ecological integrity/threat; potential cullity to the inclusion or estimation of certain ecosystem services	Uncertain adoption by government development plans; inconsistent implementation between regions or contexts

provisioning, (iii) water regulation, (iv) climate regulation, (v) flood mitigation, (vi) landslide mitigation, and (vii) fire mitigation. Future ECCAs, either in Seryuan District or other districts, could well reflect a different set of the 18 prescribed ecosystem services, according to local priorities and analytical capacities.

For each ecosystem service separately, the ECCA employed a spatially-explicit index to quantify the capacity of a given unit of land to sustain the ecosystem service. The index is defined by the weighted sum of scores for the classes of each of three categorial variables—*landscape type* (e.g., alluvial plain, peatland, karst hill, denuded mountain, etc.), *vegetation type* (e.g., lowland dipterocarps, limestone forest, mangrove, etc.), and *land cover type* (e.g., primary dryland forest, shrub, plantation, settlement, etc.), each observed spatially at 1:250,000 scale (GIA, 2016; MoEF, 2019a). Higher index scores denote a greater capacity for sustainable ecosystem service provision. Formally, the index, hereafter termed the Environmental Service Index (ESI_j) for a given ecosystem service *j,* is given by Eq. 1:

$$ESI_j = (w_s \times s_s) + (w_v \times s_v) + (w_c \times s_c) \quad (1)$$

where, for ecosystem service *j:*

$s_s, s_v, and\ s_c$ denote the scores for each class of the variables *landscape type*, *vegetation type*, and *land-cover type*, respectively, and

w_s, w_v, and w_c denote the weights for each class of the variables *landscape type*, *vegetation type*, and *land-cover type*, respectively.

Thus, for each ecosystem service *j* separately, scores and weights are combined to create one ESI_J index value for a given spatial unit of observation.

Scores reflect the influence of each class of each variable to provide environmental services generally. Each class of each variable has a different score of range 1–5, where 1 and 5 denote the lowest and highest capacity to provide environmental services, respectively. Unlike scores, weights for the classes of variables *vegetation type*, *landscape type*, and *landcover type* vary between the seven ecosystem services observed here. Variation amongst the weights serves to recognize the varying relative importance of one variable compared to another in the context of a given ecosystem service *j*. The sum of weights is equal to 1.

The *ESI* of Eq. 1 thus describes a non-denominational index of the potential for a given area to sustainably provide ecosystem service *j,* where the area in question is defined by the spatial intersection of the classes of the variables *landscape type, vegetation type*, and *land-cover type*. Supplementary Information S1 reports the scores and weights for each class of each variable for each of the seven ecosystem services considered here. Index values for ecosystem service *j* were subsequently classified into five classes of HCV-area likelihood: very low (1–1.8), low (1.81–2.6), moderate (2.61–3.4), high (3.41–4.2), and very high (4.21–5), where the threshold ESI_j values defining these classes reflected official guidance (MoEF, 2019b). HCV areas for Seruyan District are designated wherever *ESI* value was "high" or "very high" for a given ecosystem service *j*. Hereafter, HCV areas identified by either "high" or 'very high' *ESI* values are denoted as "higher confidence" HCV areas, and all other HCV areas are denoted as "lower confidence".

Scores and weights for each class of the three variables of Eq. 1 were initially determined by expert opinion gathered via a series of focus-group discussions. Experts consisted of principal environmental scientists of the Indonesian Institute of Science as well as local academics, all of whom have knowledge of and experience with environmental assessment and were involved in the development of the ECCA guidelines (MoEF, 2019b). Focus groups sought to ascribe scores and weights by consensus amongst participating experts. For a given ecosystem service, the experts discussed and determined scores and weights based on the role of a given class or variable in providing the ecosystem service. This approach sought to recognize the highly uneven potential for ecosystem service provision amongst the classes of a given variable. For instance, the ecosystem service of fire mitigation is minimal on degraded and cultivated lands, where most burning occurs (Ravi et al., 2009), and conversely it is maximal in closed-canopy forests, where burning is rare (Nikonovas et al., 2020). Similarly, the multi-variate nature of the *ESI* index allows for relatively nuanced determinations of HCV-area likelihood. For instance, whereas peatland generally burn extensively (Sloan et al., 2022), and so might merit a low score for fire mitigation, areas of primary peatswamp forest within peatland landscapes would still have a high mitigating effect (Nikonovas et al., 2020), increasing local fire-mitigation scores accordingly. Following the focus groups, the scores and weights were expressed cartographically to solicit feedback from a broader audience of government representatives, local academics, and environmental practitioners engaged with environmental assessments and ECCAs. Feedback typically entailed the affirmation of the original scores and weights; only rarely were they adjusted.

2.4 HCV screening

HCV Screening is a desktop analysis used to identify and prioritize potential HCV areas for protection at regional scales. First outlined in 2019 and then updated in 2020 by the HCV Network (Watson, 2020), HCV Screening adopts HCV assessment methods developed at the concession level (Areendran et al., 2020) but scales their application to the jurisdictional level. HCV Screening protocols therefore purport a more regionally holistic or consistent approach to HCV assessment than standard, concession-level assessments (Watson, 2020). Unlike HCV areas identified by the ECCA, HCV areas identified by HCV Screening are not based on land-use planning regulations particular to Seruyan District, notwithstanding an explicit recognition of legally protected areas or similar, such as national parks or designated production forests (Table 1). Also, in contrast to the ECCA, the HCV Screening method disaggregates the total HCV area into six thematic classes, labelled HCV 1 though to HCV 6 in Table 2, pertaining to endangered species, ecosystem services, and community needs, amongst other themes.

HCV Screening as realised here entailed a straightforward two-stage process. In the first stage, available secondary spatial data and contextual information (i.e., reports, published studies, official spatial data) pertaining to key indicators of HCV areas were compiled for each HCV thematic class (Table 3). For example, spatial data on remnant forest cover (MoEF, 2019a) and endangered orangutan sightings (Santika et al., 2017) were compiled and considered as indicators of the HCV 1 class (rare, threatened, endangered species) (Table 3). In this study, we consider only HCV thematic areas of classes HCV 1 through HCV 4 (Table 2),

TABLE 2 Six thematic classes of High Conservation Value as per the HCV Screening method.

Class		Description
HCV 1	Rare, threatened, endangered species	Concentrations of biological diversity, including endemic, rare, threatened, or endangered species
HCV 2	Landscape-level ecosystems	Large landscape-level ecosystems, ecosystem mosaics, and Intact Forest Landscapes (IFL), which contain viable populations of the great majority of naturally-occurring species
HCV 3	Rare, threatened, endangered ecosystems and habitats	Rare, threatened, or endangered ecosystems, habitats and refugia
HCV 4	Ecosystem services	Basic ecosystem services in critical situations, including protection of water catchments and control of erosion of vulnerable soils and slopes
HCV 5	Community needs	Sites and resources fundamental for satisfying the basic necessities of local communities or indigenous peoples (for livelihoods, health, nutrition, water, etc.)
HCV 6	Cultural values	Sites, resources, habitats and landscapes of global or national cultural, archaeological or historical significance, and/or of critical cultural, ecological, economic or religious/sacred importance for local communities or indigenous peoples

Source: Watson (2020).

which pertain exclusively to environmental conditions, since their remit corresponds most closely with that of the ECCA.

In the second stage, a threshold value/class was determined for each HCV indicator, based on the literature and/or expert opinion, to distinguish areas with higher versus lower likelihoods of HCV area (Table 3). For example, since remnant forest fragments >12,500 ha are deemed able to support viable populations of Borneo orangutans, fragments greater than this threshold were designated of a higher likelihood of HCV for the HCV 1 class, while those less than this threshold were designated as a lower likelihood of HCV (Watson, 2020). Indicator thresholds were typically described by a simple binary state, such as for (a) the presence or absence of a given indicator (e.g., a Ramsar site), (b) the occurrence of natural or non-natural vegetation of interest (e.g., wetlands, peatlands), or (c) by the presence or absence of a buffer distance around a feature of interest (e.g., rivers) (Table 3). For a given HCV thematic class as a whole (e.g., HCV 1), a higher likelihood of HCV area is said to occur when at least one HCV indicator is of a higher likelihood. Similarly, for all four HCV thematic classes considered here (i.e., HCV 1 through HCV 4), a HCV area is said to be of a higher likelihood when any indicator of any HCV class is of a higher likelihood. Hereafter, HCV areas identified as a 'higher likelihood' are denoted 'higher confidence' HCV areas, and otherwise as 'lower confidence' HCV areas, for consistency with the ECCA terminology.

2.5 Higher confidence HCV areas of the ECCA versus HCV screening

While the ECCA and HCV Screening methods both emphasise similar aspects of similar environmental features or conditions, e.g., intact forests, they clearly also differ in various respects, empirically, methodologically, and conceptually. Such differences between ECCA and HCV Screening would manifest as differences to the HCV areas identified by each methodology, perhaps especially with respect to higher-confidence HCV areas meant to prioritise jurisdictional vetting of potential HCV areas. At least two key differences between the ECCA and HCV Screening methods are apparent. First, HCV Screening explicitly prioritises areas that are nominally natural, intact, critical habitat, and/or biodiversity rich, whereas the ECCA does not. In this study, HCV Screening reflects distributions of threatened orangutans, as well as the presence of biodiversity-rich Ramsar sites and protected areas (Table 3). The current ECCA did not quantify biodiversity as an ecosystem service, though future ECCAs will likely do so. Second, the ECCA reflects a relatively wide range of ecosystem services and is relatively disposed to recognise their provision in human-modified, semi-natural landscapes, depending on the service. Fire mitigation and climate regulation, in particular, are afforded to moderate or high degrees by many modified landscapes, e.g., production forests, which might be discounted by HCV Screening for lack of strictly natural, intact forest. Higher-confidence HCV areas according to each method are compared directly in Section 3.

3 Results

3.1 HCV areas of the ECCA vs. HCV screening

The ECCA and HCV Screening methods produced very similar delineations of overall HCV area. Whereas the ECCA method classified 92% of Seruyan District as potential HCV area (Figure 2A), the HCV Screening method classified 87% as potential HCV area (Figure 2B). Both methods designated a common 87% of the district as HCV area (Figure 3A) and had a similarly high level of agreement across oil-palm and forestry concessions overall (Figures 4A, B). This strong agreement of overall HCV area between the two methods (Figure 3A) is due to the fact that, nominally, most of Seruyan District is HCV (Figure 2), including in many cleared and/or concession areas (Figures 4A–D). These results are consistent with a precautionary approach to initial HCV-area identification whereby designated HCV areas are ultimately validated as such, as via field visits, prior to their final adoption for jurisdictional land-use planning.

Forestry and agricultural concessions featured prominently in HCV-area designations. HCV areas designated by both the ECCA

TABLE 3 Indicators of HCV thematic classes HCV 1-4 and the likelihood of their presence (confidence classes) modified from HCV Screening guide (Watson, 2020) in Seruyan District.

HCV indicator	Higher confidence of HCV presence	Lower confidence of HCV presence	Data source
HCV 1—Rare, threatened, endangered species			
Protected areas (protected forest, conservation areas)	With natural forest cover	With no forest cover	Seruyan District Spatial Planning Regent of Seruyan Decree (2019)
Patch size of natural forest	≥ 12500 ha	> 250 ha and < 12500 ha	Official land-cover maps MoEF (2019a)
Orangutan population	Estimated > 200 orangutans within village administrative boundary with natural forest cover	Estimated > 200 orangutans within village area with non-forest natural vegetation	Orangutan population Santika et al. (2017); Land cover MoEF (2019a); Administration boundary GIA (2016)
Riparian area	1 km buffer of Seruyan River, or 100 m buffer of other rivers and lakes, with natural forest cover	1 km buffer of Seruyan River, or 100 m buffer of other rivers and lakes, with non-forest natural vegetation	River and lake map GIA (2016)
HCV 2—Landscape-level ecosystems			
Intact Forest Landscape (IFL)	Areas which qualify as IFL	Areas that are not IFL	Intact Forest Landscapes (https://intactforests.org/)
Ramsar sites	Ramsar wetland	Not Ramsar wetland	Ramsar Sites Information Services (https://rsis.ramsar.org/)
Wetlands	Wetlands with natural forest cover area (primary and secondary swamp forest)	Degraded wetlands	Official land-cover maps MoEF (2019a)
Production forest	With natural forest cover patches >100 ha	With natural forest cover patches <100 ha	Seruyan District Spatial Planning Regent of Seruyan Decree (2019)
HCV 3—Rare, threatened, endangered ecosystems and habitats			
Natural Forest	Covered by natural forest	Covered by non-natural forest cover (e.g., plantation)	Official land-cover maps MoEF (2019a)
Existing Mangrove	Intact/healthy mangroves	Degraded, fragmented mangroves	Official land-cover maps MoEF (2019a)
Swamp Area	Intact/healthy swamp area	Degraded, fragmented swamp	Official land-cover maps MoEF (2019a)
Peatland	With natural forest cover	Degraded/drained peatland	Peatland maps MoEF (2019a); Official land-cover maps MoEF (2019a)
HCV 4—Ecosystem services			
Wetlands	Intact/healthy wetlands	Fragmented, potentially polluted, wetlands	Official land-cover maps MoEF (2019a)
Steep slope areas	Slopes of > 40% with natural forest cover	Slopes of 25%–40% with natural forest cover	SRTM data Jarvis et al. (2018); Official land-cover maps MoEF (2019a)
Swamp areas	Present	Absent	Official land-cover maps MoEF (2019a)
River	River ≥ 50 m width, good water quality	River < 50 m width, polluted, suffering siltation	River map GIA (2016)
Lake	Permanent Lake	Seasonal Lake	Lake map GIA (2016)

and HCV Screening were extensive across the district's oil-palm, logging, and mining concessions (Figures 4A, B). Also, virtually all of the HCV areas identified by the ECCA but not HCV Screening (Figure 3B), comprising 5% of the district, are located within oil-palm concessions in central Seruyan District (Figure 4A). Similarly, virtually all of the higher-confidence HCV areas identified exclusively by the ECCA (Figure 3B) are located within the oil-palm concessions in central Seruyan District (Figure 4C). This concentration of HCV areas unique to the ECCA within oil-palm concessions (Figures 4A, C) is seemingly due exclusively to high *ESI* values for the fire mitigation (Figure 6G) and/or climate regulation (Figure 6D) ecosystem services, identified below as factors of disproportionate influence to the ECCA HCV-area delineation (Section 3.2).

The geography of HCV areas according to the ECCA poses political challenges for implementation or, indeed, opportunities for its derailment. The near ubiquity of all HCV areas across the district (Figure 2) and its concessions (Figures 4A, B) would likely prove excessively onerous and politically fraught for any land-use planning that would seek to recognise all such HCV areas. A validation of the nominal HCV areas prior to their official adoption would prove essential in this respect, both to cull the total HCV area and buttress any decision to conserve particular HCV areas. Further, in contrast

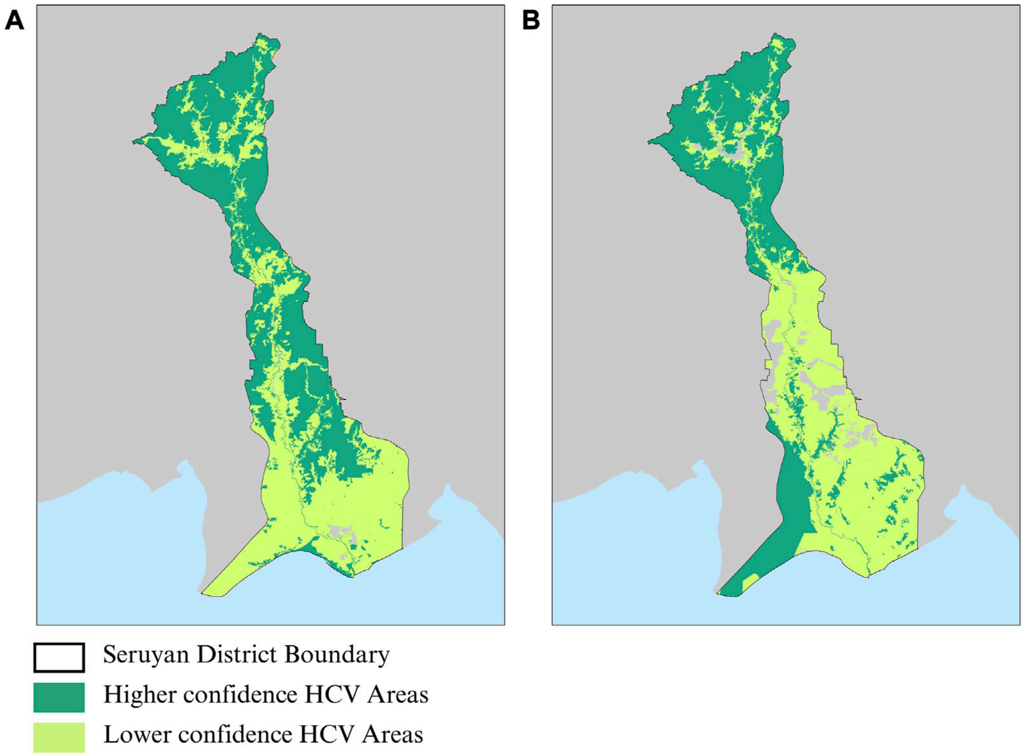

FIGURE 2
HCV areas of lower and higher confidence accord to **(A)** the Environmental Carrying Capacity Assessment and **(B)** HCV Screening.

to the ubiquity of all HCV areas (Figure 2), higher-confidence HCV areas exhibited much greater disagreement between the ECCA and HCV Screening methods (Figure 3), particularly within oil-palm concessions (Figures 4A, C). Although the ECCA and HCV Screening method both designated roughly half of the district as higher-confidence HCV area, at 51% and 42%, respectively, the proportion of these extents exclusive to a given method was appreciable, at 45% for the ECCA [all of which occurs in oil-palm concessions (Figure 4C)] and 35% for HCV Screening. The fact that these discrepancies are centered on oil-palm concessions could conceivably be exploited by vested interests seeking to challenge the basis of ECCA HCV areas. Once again, a validation of HCV areas would be essential to ensure politically feasible conservation.

3.2 HCV areas of the ECCA by ecosystem service and bioregion

The ECCA underlying HCV-area designations is highly sensitive to 'capture' by a single ecosystem service and/or the estimation of its *ESI,* as indicated by marked dissimilarities between the frequency distributions and geographies of *ESI* values amongst the seven surveyed ecosystem service. In general, the capacity for ecosystem-services provision was greater in the northern, forested, upland region of the district than in its relatively deforested central and southern lowlands (Figures 5, 6), which are dominated by oil palm (Figure 4A). However, the ecosystem services of climate regulation, and especially fire mitigation, were notable exceptions to this geographical pattern, given their near-ubiquitous "high" and "very high" *ESI* values, respectively (Figures 6D, G; Figure 7). Correspondingly, these two ecosystem services alone would account for 84%–93% of the total HCV area estimated for the district by the ECCA (Figure 2A). Similarly, the frequency distributions of the five *ESI* classes ranging from "very low" to "very high" vary drastically between the seven ecosystem services considered by the ECCA (Figure 7). Whereas only 3%–18% of Seruyan District would merit HCV-area designation on the basis of *ESI* values for water regulation, water provision, or food provision, some 65%–93% of the district would merit HCV-area designation on the basis of *ESI* values for the remaining ecosystem services, again especially climate regulation (84%) and fire mitigation (93%) (Figure 7).

The near ubiquity of high and very high *ESI* values for climate regulation and fire mitigation are not necessarily suggestive of an imprecise or 'exaggerated' *ESI* estimation. Indeed, there is no reason to expect comparable geographies or frequency distributions of *ESI* values across the ecosystem services within any jurisdiction. Amongst the seven ecosystem services considered here, large discrepancies in their frequency distributions and geographies do however underscore how a single ecosystem service with near-ubiquitously higher *ESI* values (e.g., Figure 6G) may alone underlie HCV-area designations across an entire jurisdiction (Figure 2A). Such

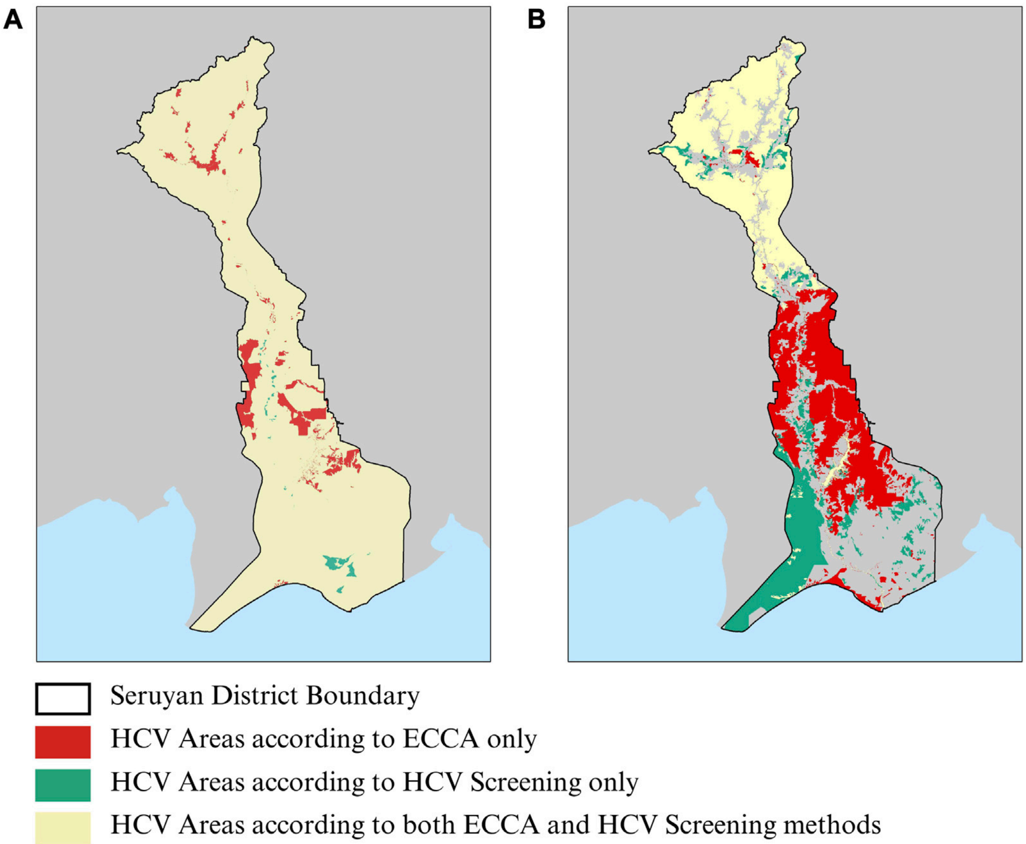

FIGURE 3
Agreement of HCV areas identified by either the Environmental Carrying Capacity Assessment or the HCV Screening method, for **(A)** all HCV areas and **(B)** higher confidence HCV areas.

an outcome is equally possible for HCV Screening, provided discrepancies amongst its four HCV thematic classes, but is not apparent here (Figure 8). Such a case of "capture" by a relative few ecosystem services would still be in keeping with the precautionary principles of HCV designation (Areendran et al., 2020), but would also drastically increase the potential for subtle but significant manipulations of the parameters of the ECCA by vested economic or political interests.

3.3 Jurisdictional authority for HCV-area management

HCV-area designation according to the ECCA or similar jurisdictional approaches to commodity supply-chain certification are challenged by spatial disagreements between HCV areas and the administrative authority of local government. In Indonesia, district-level governments have exclusive jurisdiction over lands legally designated for agricultural or similar non-forestry land uses outside the official Forest Estate. Hence, the Seruyan District government would have jurisdiction over HCV areas within its oil-palm concessions, and areas of potential oil-palm concessions, which by law are granted on lands outside of the Forest Estate. The district government would have no jurisdiction over HCV areas within logging concessions, or potential logging concessions, as these concessions are granted within the Forest Estate.

Of the total HCV area designated by the ECCA in Seruyan District (Figure 2A), only 22% falls under the immediate and sole administrative authority of the district government (Table 4). Such areas are relatively devoid of intact forest cover and disproportionately orientated towards agricultural concessions, as expected. The remaining 68% and 9% of nominal HCV areas fall under the administrative jurisdictions of the provincial and national governments, respectively (Table 4). These areas are relatively forested and encompass forest concessions. ECCA areas falling under national jurisdiction occur within nature reserves and protected areas, e.g., national parks, which are managed by the national Ministry of Environment and Forestry. HCV areas under provincial jurisdiction similarly occur within forests legally designated for protection, production, or conversion that here are presumed to have operational forest management units, i.e., community-minded cooperative forest management administrations (Sahide et al., 2016a). While these areas of legally designated forest use are originally under the jurisdiction of the national Ministry of Environment and Forestry, authority over forest management units devolves to a supervisory provincial government.

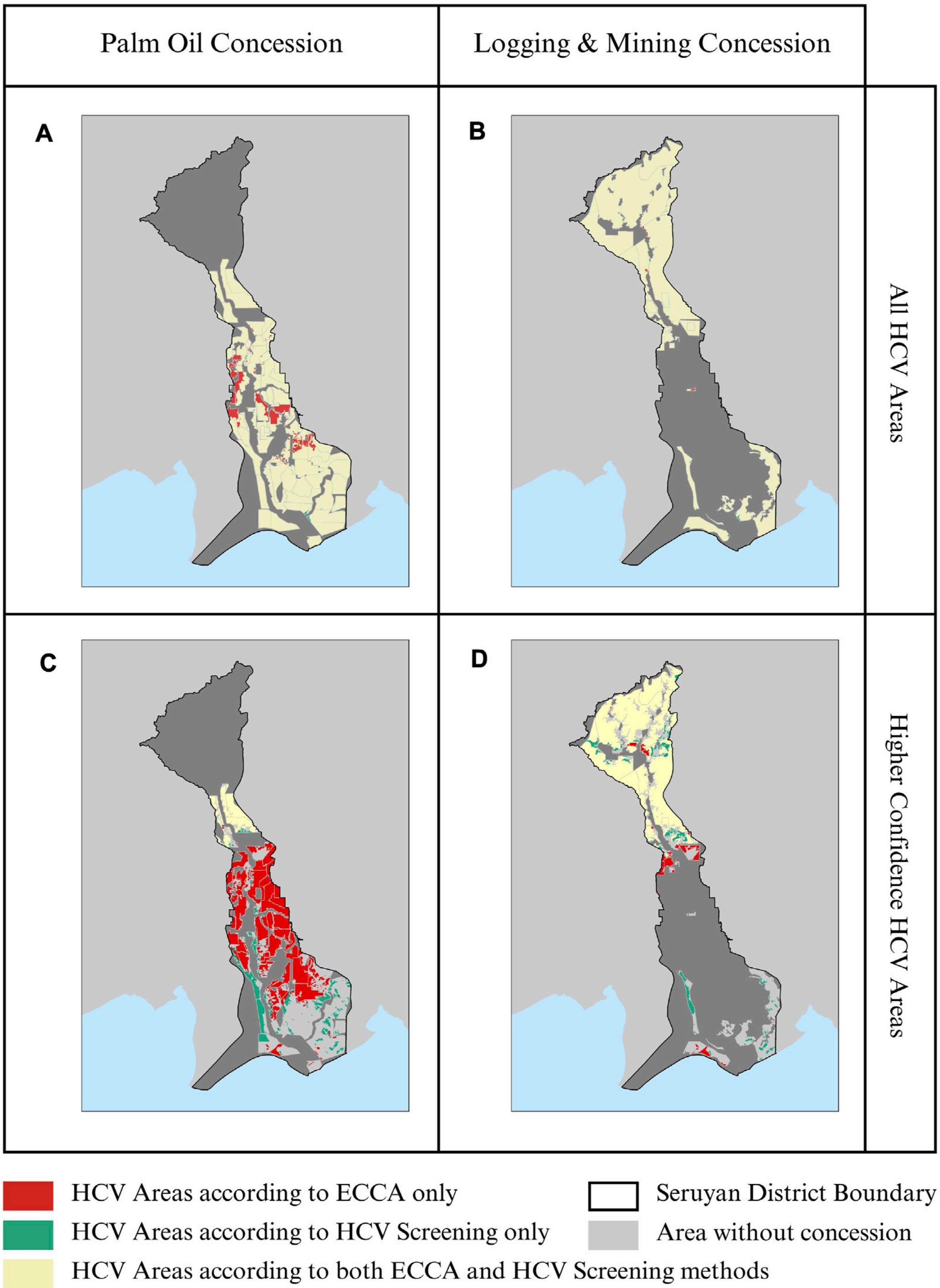

FIGURE 4
HCV area distribution within concessions, by method of HCV identification and HCV confidence class: All HCV area within palm-oil concessions **(A)**, All HCV area within logging and mining concessions **(B)**, Higher confidence HCV area within palm-oil concessions **(C)**, Higher confidence HCV area within logging and mining concessions **(D)**.

In summary, the Seruyan District government would have exclusive authority to recognize HCV areas within its oil-palm production zones, but would have little to no authority in other, relatively forested, and often adjacent conservation and forestry zones, which host 72% of higher-confidence HCV areas across the district (Table 4; Figure 2A; Figures 4A, C). Such uneven jurisdictional geography in relation to forest extent and concession type would necessitate inter-governmental cooperation for truly district-wide, coordinated HCV management.

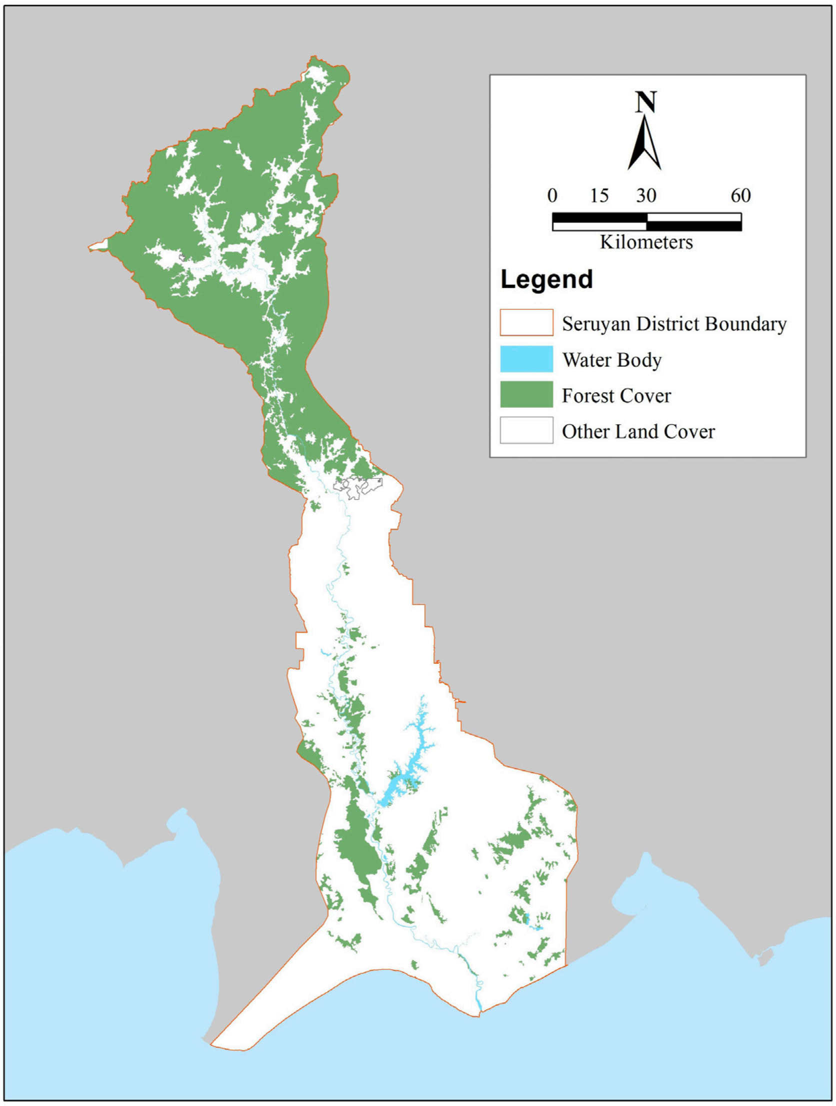

FIGURE 5
Forest cover in Seruyan District. Source: MoEF (2019a).

4 Discussion

4.1 Jurisdictional approaches and certifiably sustainable commodity supply chains

Protecting the world's remaining natural terrestrial ecosystems requires halting deforestation and degradation caused largely by agricultural commodity supply chains (Austin et al., 2017a; 2017b; Garrett et al., 2019). Current approaches to reducing commodity-driven deforestation focus on identifying sites of deforestation, linking these to 'downstream' agents in supply chains (e.g., mills, exporters), and documenting how international companies further downstream in the supply chain are connected to these sites and agents (Gardner et al., 2019). Companies implicated by supply chains can either choose to improve the environmental standards of their upstream suppliers, or they can exclude suppliers with environmentally destructive practices (Lambin et al., 2018). Commodity certification schemes, such as RSPO, offer pathways for companies to improve the sustainability of production while offering assurances to buyers regarding which companies to patronize (Loconto and Fouilleux, 2014; DeFries et al., 2017; Lambin and Thorlakson, 2018).

Notwithstanding well-established supply chain certification schemes for certain commodities, such as timbers, there remains appreciable variation in scheme effectiveness among commodities and regions (Seymour and Harris, 2019), and commodity-driven tropical deforestation apparently remains undiminished overall (Curtis et al., 2018). Reasons given for the apparent ineffectiveness of current supply chain certification models are largely economic. They include the limited adoption of certification schemes due to limited markets for certified products (Tayleur et al., 2018; Tayleur et al., 2017); a low marginal price increment for certified commodities, especially at the farm gate (VanWey and Richards, 2014; Tey et al., 2020); and low demand for certified commodities among key buyer countries, especially China and India (Schleifer and Sun, 2018). Political and

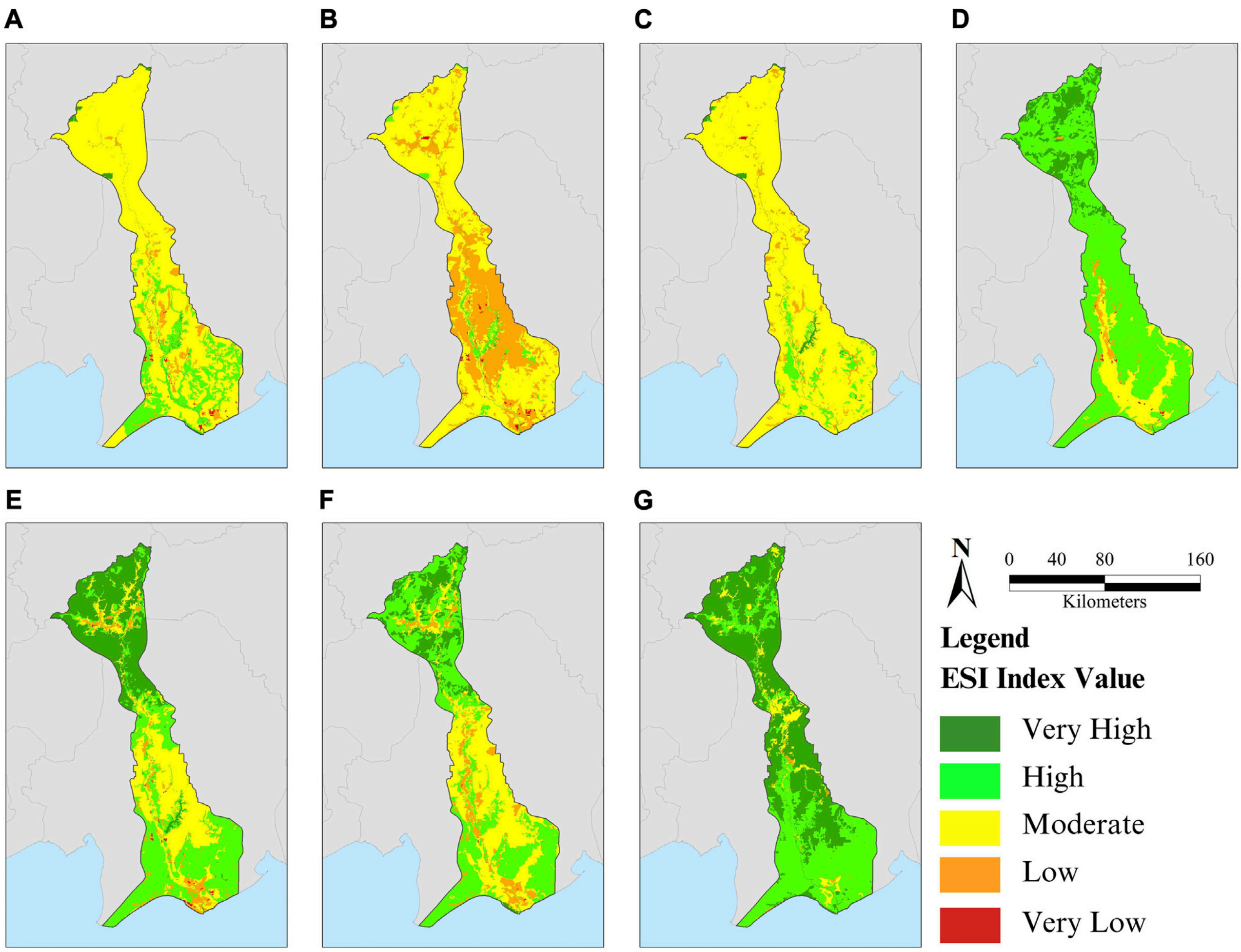

FIGURE 6
Environmental carrying capacity assessment results in Seruyan District with respect to the geography of seven ecosystem services: **(A)** water provisioning, **(B)** food provisioning, **(C)** water regulation, **(D)** climate regulation, **(E)** flood mitigation, **(F)** landslide mitigation, and **(G)** fire mitigation.

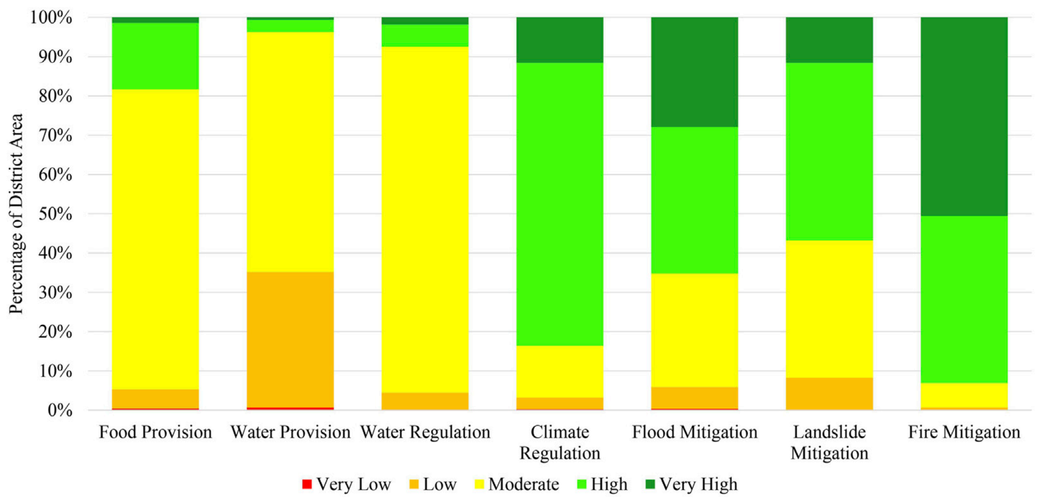

FIGURE 7
Environmental carrying capacity assessment results in Seruyan District with respect to the frequency distribution of carrying capacities for seven ecosystem services.

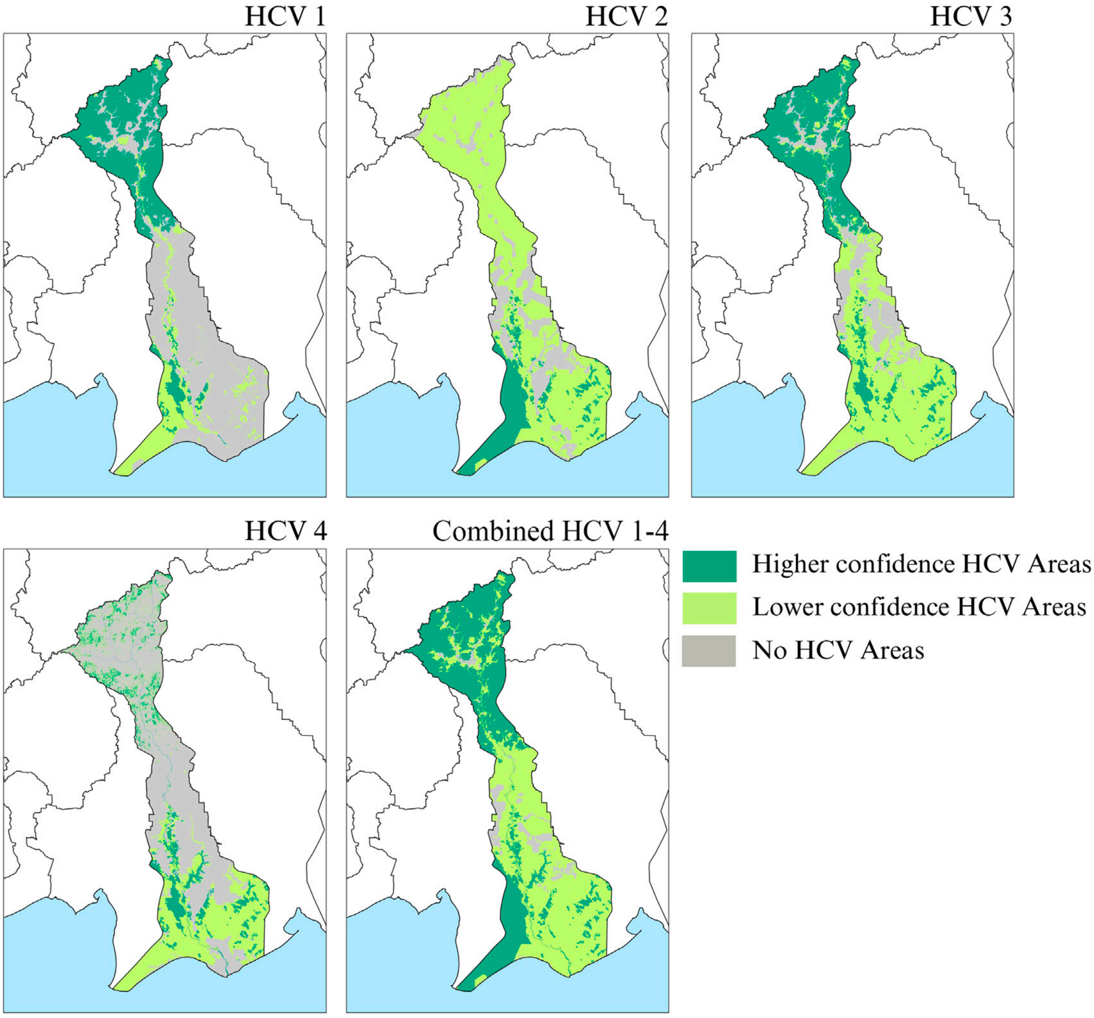

FIGURE 8
The distribution of the four HCV thematic classes of HCV Screening in Seruyan District, individually (HCV 1, HCV 2, HCV 3, HCV 4) and combined (HCV 1–4), by HCV confidence. Notes: Areas of classes HCV 1-4 by HCV confidence level are reported in Supplementary Information S4.

TABLE 4 HCV area identified by the ECCA, by level of government with jurisdiction over the HCV area.

Governmental level	Percentage of HCV area in Seruyan district		
	Lower confidence HCV	*Higher confidence HCV*	*Total HCV*
District	8.0	14.2	22.2
Provincial	31.5	36.6	68.0
National	8.6	0.4	9.0

corporate marketing initiatives are however arguably shifting such economic factors. Consumer countries, especially in Europe, have begun introducing regulatory requirements intended to prevent unsustainable commodities from entering their markets (Sellare et al., 2022). Similarly, in response to consumers' perceived weaknesses of certification schemes, their environmental criteria have sometimes been made more stringent, as when the RSPO introduced no-deforestation and no-exploitation commitments for peatlands in 2018 (Jong, 2018). Such political and corporate initiatives are still nascent, and their impact on the demand for certified, sustainable commodities remains unknown.

Jurisdictional approaches to certifying commodity production have been proposed as a relatively environmentally stringent and economically efficient means of reducing commodity-driven deforestation. Underpinning this approach is the fact that local governments, supported by multi-stakeholder industry groups (e.g., the RSPO), have the authority, means, and interest to reduce commodity-driven deforestation (Busch and Amarjargal, 2020; Boshoven et al., 2021; Essen and Lambin, 2021). Initially promoted in Latin America with a focus on soy and cattle (Nepstad et al., 2014; Nepstad et al., 2013), jurisdictional approaches to sustainable commodity production have proliferated globally and now encompass a range of commodities, including palm oil, cocoa, timber, and pulp and paper (Seymour et al., 2020; Essen and Lambin, 2021). The resultant plurality of jurisdictional approaches and commodities means that there is no single standard for measuring the soundness of jurisdictional approaches and, consequently, whether commodities sourced from certified regions can credibly be deemed to be sustainable. This is in contrast to conventional, non-jurisdictional supply chain certification schemes whereby principles, criteria, and indicators for sustainable production at a given site are explicitly delineated, often by multi-stakeholder groups such as the RSPO or the Forest Stewardship Council (Loconto and Fouilleux, 2014).

Our findings demonstrate that a careful adoption of an existing regulatory instrument, here the ECCA, to scale the principles and criteria of supply-chain certification schemes (RSPO, 2021a), can produce results similar to current best-practice approaches to this same end, namely, HCV Screening (Watson, 2020). Although the ECCA regulatory instrument focused on one element of the RSPO Principles and Criteria, namely, the identification and protection of HCV areas (Areendran et al., 2020), a similar approach is conceivably possible for other environmental, social, and governmental aspects of these principles and criteria (Pacheco et al., 2020). The legality and legitimacy of the ECCA, and its alignment with official land-use planning and environmental-management processes, increase the likelihood that HCV areas will be officially adopted and efficiently protected. This process of transitioning from an ECCA to vetted, protected HCV areas is not exact, nor even assured, however. Below we identify several factors contributing to uncertain or inefficacious transitions.

4.2 Transitioning from regulatory instrument to HCV area

In a given jurisdiction, a regulatory instrument adapted to support jurisdictional supply-chain certification may well have been originally designed for very different purposes and so may prove to be of limited relevance to HCV identification *per se*. In the case of the ECCA, it is based on a supply-and-demand approach to ecosystem-service assessment, whereby environmental carrying capacity is said to be exceeded when the estimated supply for ecosystem services exceeds the estimated demand (Świąder et al., 2020a; Nepstad et al., 2020b). In contrast, the HCV Screening approach focused on HCV areas defined from a conservation perspective, supplemented with consideration of land use and potential threats to habitat (Senior et al., 2015; Areendran et al., 2020). Despite these methodological differences, the ECCA provided results similar to those of the HCV Screening in terms of overall HCV area, notwithstanding discrepancies observed amongst higher-confidence HCV areas. The similarity of overall HCV areas may simply reflect the fact that each method designated the vast majority of our study district as HCV area (Figure 2), which may not be the case elsewhere or for other regulatory instruments. Further, in the case of our ECCA, the extensiveness with which it designated HCV areas was highly dependent on the particular selection and/or estimation of ecosystem services, of which two alone (fire mitigation and climate regulation) could account for nearly all HCV areas (Figure 6).

A further consideration for the transition from regulatory instrument to HCV area is, obviously, the administrative scale of the regulatory instrument. Indonesia provides an illustrative example regarding sustainable oil-palm certification. An Indonesian regulatory instrument seemingly more aligned with HCV designation than the ECCA is the Essential Ecosystem Areas (EEA) instrument, which seeks to identify and protect important ecosystems outside conventional conservation areas (Sahide et al., 2020). The EEA instrument falls under the authority of the federal Indonesian Ministry of Environment and Forestry, with management devolved to provincial governments, such that district governments have neither authority for EEA designation nor management (Steni, 2021). Consequently, although thematically aligned with HCV conservation, EEAs cannot be used for oil-palm certification at the district level, at least not directly, despite oil-palm concessions being granted and managed by district governments. Land-use planning (i.e., spatial planning laws) and similar district-level instruments, including ECCAs, do however allow district governments to designate Strategic Environmental Areas (SEAs) that are similar to EEAs. The utility of SEAs and EEAs for HCV designation merits consideration in the future.

Finally, the choice of regulatory instrument must consider that the instrument, or its administration, may not grant jurisdictional authority over many of the HCV areas that the instrument would ultimately designate. In the case of the ECCA in Seruyan District, 77% of the total HCV area identified (Figure 2A) fell within the Indonesian Forest Estate, the administration of which is beyond the authority of the district government (Brockhaus et al., 2012; Sahide et al., 2016b). Ironically, the management of only those HCV areas falling under the jurisdiction of the district government would likely engender the same critiques of disjointed, piecemeal conservation as levelled previously against conventional RSPO certification realized at the concession scale. Although district governments cannot directly manage most forests and protected areas, they can support forest and habitat integrity through the creation of buffer zones (Jotikapukkana et al., 2010) and ecological corridors (van Noordwijk et al., 2012). Perhaps especially in Indonesia, where environmental governance is relatively decentralised and closely reflects the geography of forest resources, a major challenge for any jurisdictional approach to HCV identification is whether a local government has the authority to manage designated HCV areas and, if not, whether intergovernmental cooperation is likely to be effective.

5 Conclusion

A jurisdictional approach to the certification of sustainable palm oil supply chains aims to apply RSPO principles and criteria for sustainable production at the scale of local governmental environmental regulation and planning. To ensure compliance with these principles and criteria, High Conservation Value (HCV) areas must be identified and protected across the jurisdiction, at least in areas eligible for oil-palm production, ideally seamlessly with environmental planning. Here, for an Indonesian district piloting jurisdictional approaches to RSPO certification, we adopted its Environmental Carrying Capacity Assessment (ECCA) to illustrate how, and how well, an existing regulatory instrument may identify likely HCV areas compared to the conventional HCV Screening method currently recommended for jurisdictional certification (Watson, 2020). Such use of existing regulatory instruments for HCV-area designation aspires to correct for key shortcomings of conventional RSPO certification, including its piecemeal implementation and poor integration with the local environmental regulation.

Our results indicate that the overall HCV-area designation according to the ECCA is geographically virtually equivalent to that based on HCV Screening. For each method, HCV areas spanned virtually the entire district, underscoring how initial HCV delineations require vetting and validation prior to official adoption, and how any ambitious adoption of all HCV areas would likely prove impracticable. In contrast, higher-confidence HCV areas according to the ECCA spanned roughly half of the district, were largely discrepant from higher-confidence HCV areas of the HCV Screening method, and uniquely spanned oil-palm concessions.

The Seruyan District government has exclusive authority over ~40% of all high-confidence HCV areas, which occur within zones of current or potential oil-palm production. The remaining ~60% of higher-confidence HCV areas designated by the ECCA occurred outside the exclusive authority of the district government, in zones designated for conservation of forestry. Intergovernmental cooperation may therefore prove essential to truly district-wide, comprehensive HCV-area delineation and management.

HCV areas according to the ECCA are sensitive to the selection of ecosystem services surveyed, and to the estimation of their provision (i.e., the *ESI*). Indeed, the very set of ecosystem services surveyed by an ECCA is at least somewhat flexible according to local development priorities and analytical capacities. The selection and estimation of ecosystem services should therefore be highly transparent, and ideally aligned with sustainability certification standards, such as those of the RSPO. The sensitivity and flexibility of ECCA HCV-area designations, as well as their ubiquity or discrepancies noted above, may invite challenges by vested interests seeking to influence HCV-area designations.

We stress that our results are particular to the ECCA conducted for Seruyan district. Our finding would likely vary given a different selection of ecosystem services and/or changes to geographic and politico-legal context. Future research on jurisdictional HCV-area delineation for RSPO certification should therefore quantify the implications of variation to (a) the selection of ecosystem services inherent to an ECCA, (b) the land-cover geography of Indonesian districts implementing a JA, and (c) political-legal contexts of land-use planning, as between the three RSPO JA pilot projects underway in Sabah, Ecuador, and Indonesia.

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.

Author contributions

MP and SS shared the same contribution including conceptualization, data curation, formal analysis, methodology, validation, writing original draft, review and editing. JW involved in developing research concept, supervision, and writing the manuscript. SI and JL contributed in writing original draft, while KP provided help in data curation, formal analysis, and methodology. CW contributed in software and visualization. EW involved in methodology, manuscript review and editing, while NU in project administration and software. All authors contributed to the article and approved the submitted version.

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/fenvs.2023.1226070/full#supplementary-material

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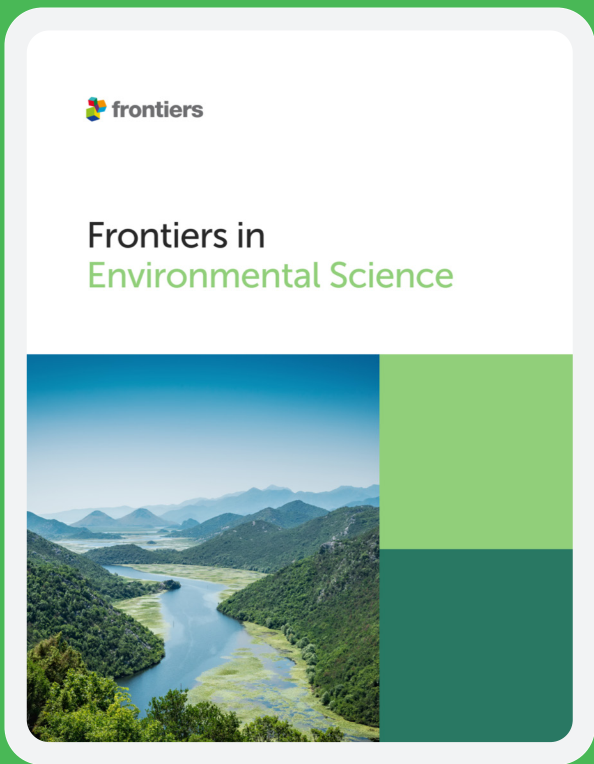

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