Frontiers in Sustainable Food Systems

Rethinking Blended High Yielding Seed Varieties and Partial-Organic Fertilizer Climate Smart Agriculture Practices for Productivity and Farm Income Gains in the Drylands of Zimbabwe

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Most blended climate smart agriculture (CSA) technologies focusing on seed-fertilizer combinations have either been marginally adopted or dis-adopted by smallholder farmers due to the nature of design and implementation. A data science research approach was used with 380 households in the mid-Zambezi Valley of Zimbabwe. The study examines impact of adopting a farmer initiated CSA practice combining improved sorghum seed variety and partial-organic fertilizer on household income and productivity among smallholder farmers in the drylands of Zimbabwe. A cross sectional household survey using multi stage sampling with purposive and stratified proportionate approaches was conducted. A structured questionnaire was utilized for data collection. Endogenous Switching Regression (ESR) model was utilized to account for self-selection bias of sampled farmers. Overall, a combination of farm specific factors (arable land, variable costs) and external factors (distance to the market, value of aid) have a bearing on the adoption decision and the associated impact on productivity and income. The counterfactual analysis shows that farmers who adopt the technology are relatively better off in productivity and income. Our findings highlight the significance of improving access to CSA practices which are initiated by the farmers using a bottom-up approach since they suit their operating contexts better. Tailor-made supporting programs including farmer networking platforms and decentralized markets need to be designed and scaled up by policymakers to encourage farmers to adopt blended soil fertility CSA practices in their farming practices. Networking arrangements need to be strengthened through local, government and private sector partnerships along the sorghum value chain.

Keywords: climate smart agriculture, farmer-centric technology, agricultural productivity, Zimbabwe, endogenous switching regression, counterfactual

THE BACKGROUND

The dominance of inappropriate agricultural practices such as improper soil preparation and management, indiscriminate use of pesticides and application of chemical fertilizers beyond the limit has persistently caused a range challenges including decrease in crop yields, soil erosion, soil salinity and pollution of water bodies. In southern Africa's agricultural value chains, this matrix of problems has culminated in reduced productivity across strategic cereal crops such as maize (*Zea mays*), sorghum (*sorghum bicolor*) and millets from on average 1.3 tons/ha to 0.9 tons/ha and lowered income by on average 23% due to a decline in the weighted average prices by 19.2% between 2015 and 2019, especially among smallholder farmers (Suresh et al., 2021). To circumvent this array of problems, there is an emerging drive toward co-designing a diverse range of resilient CSA programs with a focus on farmers taking the center stage. Climate-smart agriculture is defined as integrated pathway that enhances the management of landscapes including the cropland, livestock systems. The advent of re-orienting CSA programs has variably pushed the design and scaling up of blended modern science and Indigenous Knowledge Systems (ITK) packages across different spatial and temporal scales (Nciizah et al., 2021). These blended CSA packages entail a combination of CSA principles in a way that direct response to the context specific challenges such as access to and application of chemical fertilizers. The core CSA practices included in these blended packages include efficient irrigation, integrated pest management (IPM), different dimensions of conservation farming and manipulation of seed and other production factors such as the use of manure (Sinyolo, 2020). Globally, therefore, the adoption of climate smart agriculture (CSA) practices is also widely reported as a gateway out of the challenges of low productivity and income among smallholder farmers in the climate change exposed drylands (Kauma, 2021; Martey et al., 2021).

In the drylands of Zimbabwe, these emerging CSA strategies have however over focused on the more preferred cereal crops including maize and cash crops such as cotton (*Gossypium*) (Mkuhlani et al., 2018). Of note, are the traditional grains, including sorghum and millets, that have not been adequately and directly accommodated at all scales (Hamukwala et al., 2010; Adegbola et al., 2013; Musara et al., 2018). However, pushed by exponential decline in agricultural performance in these fragile communities and increased incidences of income deterioration, a handful of the emerging CSA interventions targeting the peripheral crops, such as sorghum seed development, financing, production and marketing support programs have been implemented by the public and private sectors post 2010 (Mapfumo, 2017). The hope is that these direct mechanisms as mentioned above will enhance sorghum productivity and income through scaled up adoption of tailor-made CSA technologies and strengthening market linkages at the different administrative, spatial and temporal scales. The acknowledgment is that, re-embracing these orphan crops and greasing their production with appropriately designed farmer-centric and market oriented CSA practices can reposition them in land allocation decisions especially in the drylands (Muzerengi and Tirivangasi, 2019).

Most of the aforementioned interventions have been designed based on a top-bottom approach, and as such, in most countries including Zimbabwe, their effectiveness has been relatively below the expectations in terms of productivity, income and food security gains (Mapfumo, 2017). This has induced lower than expected adoption with on average 30% of farmers taking up the technology against a target of above 80% (Shiferaw et al., 2013). On one hand, smallholder farmers cultivate the crops on small pieces of unproductive land averaging 0.15 hectares against an expected benchmark of 0.3 hectares, while also using low yielding varieties and recycled seed (Khonje et al., 2015; Mujeyi et al., 2021). On the other end, sorghum processors and consumers are not willing to pay competitive market prices and pay on average 11.3% below the breakeven price for the produce, thus further reducing the utility and subsequent adoption (Makindara et al., 2013). The result is that in most parts of dryland southern Africa, comprehensive understanding of the productivity and income enhancing capacity of emerging blended CSA based sorghum production practices is therefore presently missing and/or inadequately explored (Tambo and Mockshell, 2018).

There is evidence that, in southern Africa, there is a pattern where smallholder farmers are adopting a package of technologies as opposed to singular adoption which dominated during the early 1990s (Mujeyi et al., 2021; Ahmed, 2022; Baiyegunhi et al., 2022). The study seeks to contribute to this discussion by focusing on the blended high yielding seed varieties and partial-organic fertilizer[1] package that has been designed by smallholder farmers in the mid-Zambezi Valley of Zimbabwe in response to the call for CSA. To the best of our knowledge, the complementarity between improved seed and varieties and inorganic fertilizer has not adequately been tapped into from the angle of technology re-design to accommodate emerging commercial organic fertilizers and traditional grains. It remains questionable as to whether there are any productivity and income gains that may be generated from the uptake of the blended and well-targeted improved seed and organic fertilizer.

A number of studies (e.g., Ali and Abdulai, 2010; Di Falco et al., 2011; Asfaw et al., 2012; Suresh et al., 2021) have examined the impact of agricultural technologies on food security and income, but the majority focused on externally driven interventions emanating from either the government, NGOs or the private players. Those which have attempted to accommodate the fertilizer component have focused on the inorganic fertilizers (Ahmed, 2022). This has crowded out a reflection on farming community initiated technologies designed in response to emerging challenges and opportunities. Additionally, most studies targeting traditional grains (e.g., Mapfumo, 2017; Musara and Musemwa, 2020; Phiri et al., 2020), have also focused more on the food

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[1]The fertilizer is not purely organic and is produced by a Zimbabwean firm. The package was initiated by farmers in partnership with a NGO and is being promoted in 7 of the 17 wards in Mbire district of Zimbabwe. The blending idea emanated from the farmers and the NGO supports through training programmes. To the best of our knowledge, this farmer initiated technology is a first in the district which targets sorghum production.

security dimension, which does not directly support the industrialization and market based commercialization (with proxies of income and productivity) drive being advocated for by stakeholders in Zimbabwe and analyzed in this study as a gap filling effort. Furthermore, in the existing analyses, sorghum production is traditionally viewed by farmers as a system requiring minimal fertilizers. Phiri et al. (2019) reports that this mentality has subsequently spilled over to the research agenda thus delineating the fertilizer component from impact analyses.

We identify the potential of capturing this missing dimension using sorghum as a pivotal crop in the drylands of Zimbabwe due to its resilience to unfavorable conditions of short growing season, limited rainfall and high temperatures. This is motivated by the success of sorghum value chains in countries such as Tanzania (Makindara et al., 2013), Zambia (Hamukwala et al., 2010) and West Africa (Haussmann et al., 2012) that has been attributed to scaling up of farmer driven productivity-enhancing technologies. In these environments, productivity has increased by on average 34.5%, food security by 29.3% while conflicting findings have been reported for income gains within a range of 12.6-27.1% (Smale et al., 2018). The technology in this study was initiated by the local farmers and culminated in a well-structured improved seed and partial-organic fertilizer package used in the study area over the past 3 seasons. The study therefore aims to fill the gap of productivity and income impact analyses and target a blended soil fertility enhancing strategy for sorghum, which is a largely excluded crop. It further examines the impact of a farmer designed package on productivity and income, a feat that is not adequately covered in literature.

MATERIALS AND METHODS

Description of the Study Site

The study was conducted in Mashonaland Central province which is located at 16.7644° S, 31.0794° E, has an area of 28,347 km², a population of 1,152,520 which represents ∼8.5% of the total Zimbabwe population and has a human population density of 41/km² (ZimStat, 2013). The mid-Zambezi Valley of Zimbabwe is situated in the province at an altitude of between 350-600 meters on the flat plain and 1228m on the highest point. **Figure 1** shows the study area.

Mbire district is located in the Lower Zambezi Trans-Frontier Conservation Area (LZ-TFCA), and has multi-cultural communities with a low human development index (HDI) of on average 0.519. Despite poor sandy soils, erratic rainfall (averaging 300mm/annum), high temperatures (averaging 35°C) and persistent crop destruction by wildlife (accounting for more than 35% of field crop losses), households heavily depend on agriculture for subsistence and income. The major activities include crop production of mainly sorghum, cotton, rapoko (*Eleusine coracana*) (in Zimbabwe- finger millet), and pearl millet (*Pennisetum glaucum*), as well as livestock where mainly cattle and goats are reared. These integrated production systems marginally reduce the risks of extreme poverty but are however not commercialized and linked to strategic markets in surrounding towns such as Mvurwi (17.0278° S, 30.8556° E).

Data Type, Sources, and Sampling Design

A pragmatic philosophy was adopted for the study and merged both the explanatory and exploratory research approaches in a cross sectional survey design. Specifically, the study was conducted in Mbire district of Mashonaland Central Province in Zimbabwe. The district was selected since it is a dryland located in the dryland region IV and V, which receives low and erratic rainfall coupled with high temperatures. A number of climate smart agriculture practices including soil fertility enhancing options, water conservation pits and inorganic fertilizer programs have also been widely supported by the government, Non-Governmental Organizations and the private sector players. From the seventeen wards in the district, five wards, 2, 4 and 10, 12 and 15 were purposively selected and included in the study. The first four wards are the dominant sorghum producing areas in the district while Gonono and Chikafa are closer to the border with Mozambique and their inclusion offered scope for understanding decisions in communities with mixed cultures and relations. Mahuwe is centrally located in the district while Chisunga (Angwa) is at the periphery of the Mid Zambezi Region. Chitsungo is a unique Ward were sorghum production is minimal and as such would also offer insights into the non-production of sorghum. The data used in the study were collected from a survey conducted during the cropping season between January and March 2020. This was also basing on information gathered from a pre-survey conducted between March and April 2016 and a series of preliminary stakeholder consultation meetings in partnership with the French Agricultural Research Center for International Development (CIRAD). The study adopted a multistage sampling strategy starting with the purposive selection of wards and stratified proportionate selection of villages to account for the adoption and non-adoption variabilities across the villages. This culminated in the proportionate random sampling of respondents from each stratum for the survey.

The Yamane (1967) formula was utilized to determine the sample size given its simplicity and wide application in social science studies. The formula was presented as in Equation (1) below.

$$n = \frac{N}{[1+N(e^2)]} \tag{1}$$

where n is the sample size, N= is the population size, and e is the precision level for confidence interval of 95% (=0.05). This yielded 380 sorghum farmers who were then included in the study. The sample size compares relatively well with other similar studies (e.g., Abdulai and Huffman, 2014). The purposive selection was based on a criteria of guaranteeing the targeting of wards and villages where there was adoption of the targeted package of an improved sorghum seed variety and partial-organic fertilizer, while capturing the diversity of household types, landholdings, access to markets among other key factors. Proportionate stratified random sampling allowed for a representative sample to be generated while accounting for
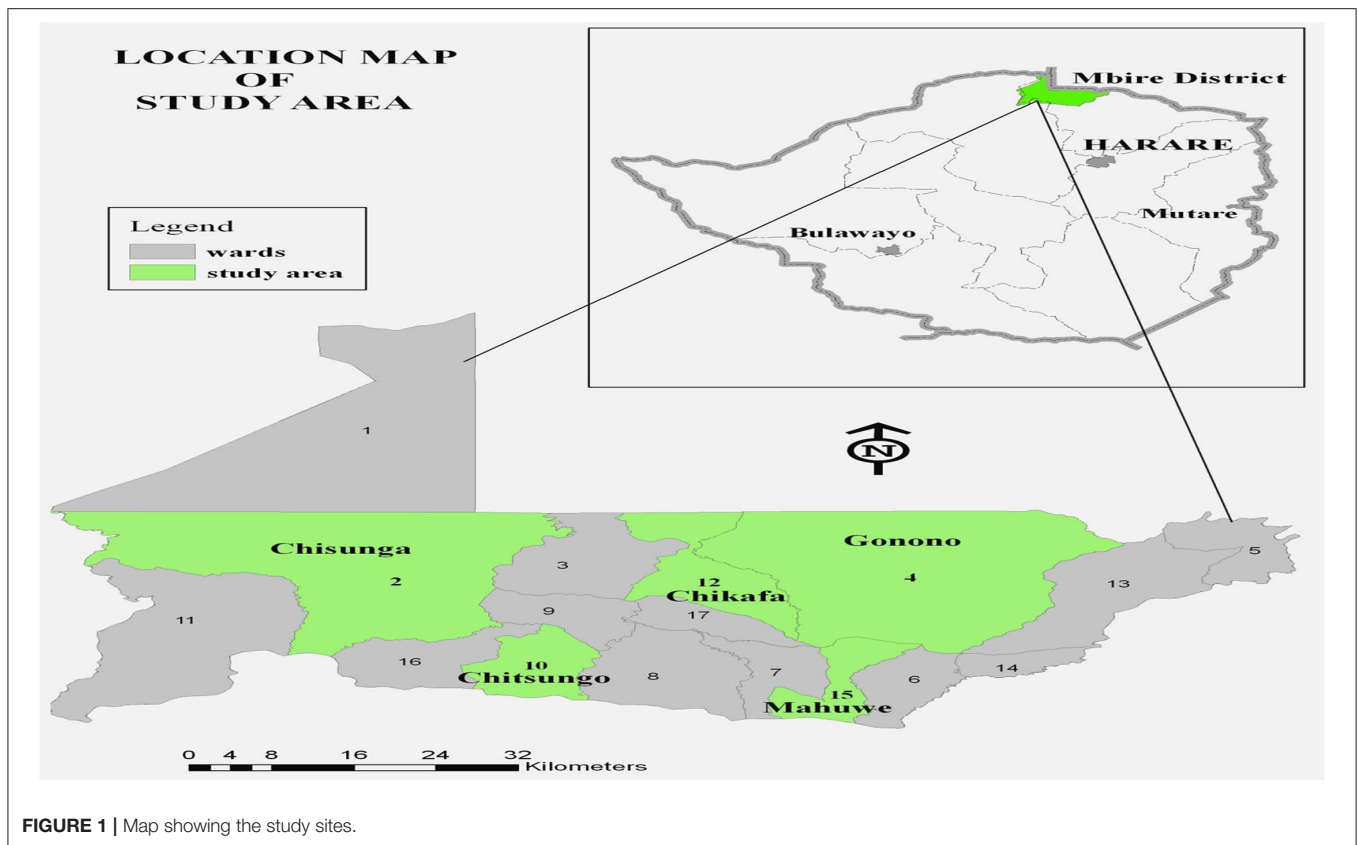
FIGURE 1 | Map showing the study sites.

TABLE 1 | Ward composition and farmer selection.

Ward[a]	Total no. of farmers	Share of farmers (%)	No. in sample
Chisunga (2)	1,580	19.18	73
Gonono (4)	1,911	23.07	88
Chitsungo (10)	1,978	23.88	91
Chikafa (12)	1,587	19.17	73
Mahuwe (15)	1,224	14.70	56
Total	8,280	100	380

[a] The ward number is placed in parenthesis.

the differences in farmer compositions across the locations of interest. **Table 1** shows the sampling strategy summary.

Detailed information was generated from the farmers using a standardized questionnaire and validated by discussions with authorities from the Ministry of Lands, Agriculture, Fisheries, Water and Rural Resettlement (MLAFWRR), mainly through local Department of Agricultural and Technical Extension Services (AGRITEX) officers. The collected data covered information on the technology's characteristics, production systems used by farmers, input access and use, transaction costs, market prices, socio-economic characteristics, and plot-level attributes. To cater for the instrument's validity and reliability, a pre-testing process was conducted. The data was captured in the STATA 13 program, cleaned, coded and analyzed.

Method of Data Analysis

Rationally, farmers consider potential benefits when making decisions to adopt emerging agricultural technologies. As such, in impact evaluation studies, researchers need to consider the nature of these technologies and avoid selection bias problems emanating from truncated observed distributions of technology outcomes (Kabunga et al., 2012). The selection bias manifests whenever the unobservable factors influence both error terms in the technology choice equation (ε) and the outcome equation (μ). This results in correlation of the error terms of the two equations, with $corr(\varepsilon, \mu) = \rho$. In this case, utilizing the generic regression techniques such as ordinary least squares (OLS) would generate biased results. Additionally, attempting to estimate the impact of the adoption decision where there is no information on the counterfactual condition would not be useful for influencing policy and practice.

Alternative Estimation Approaches

A number of alternative approaches have been widely used in technology adoption impact analyses. The Heckman two-step method has been used by some authors (e.g., Ghimire and Huang, 2015) to deal with selection bias. The major limitation sets in due to the method's inherently restrictive normally distributed errors assumption. An alternative approach of controlling for selection bias is to utilize the instrumental variable (IV) method. It is however difficult to find and identify valid instruments to include in the estimation. Additionally, in the IV process, as is the case

with OLS estimation, the linear functional form assumption does not always hold since the coefficients on the control variables may be different for adopters and non-adopters.

The propensity score matching (PSM) technique has also been extensively used (e.g., Caliendo and Kopeinig, 2008; Becerril and Abdulai, 2010) to balance the observed distributions of the covariates for the non-adoption (control) and adoption (treatment) groups. The main drawback is the Conditional Independence Assumption (CIA), which states that, for selected covariates, the adoption is independent of potential outcomes. However, selection into the treatment group, based on unmeasured characteristics, may also trigger systematic differences between the groups' outcomes, regardless of conditioning on the observables. Using PSM implies that, the estimates from the binary model (probit or logit) cannot be interpreted to imply the determinants of adoption. In the current study, we however intend to determine the adoption drivers of an emerging blended CSA technology package and the associated impact on the productivity and income. To achieve this, we utilized the endogenous switching regression (ESR) model which accounts for the selection bias on estimating the impact of adoption on the two farm outcomes of interest. The method is a generalization of Heckman's selection correction approach and captures the selection on unobservable by treating selectivity as an omitted variable problem (Lokshin and Sajaia, 2004).

The Endogenous Switching Regression Strategy

We used a two-step estimation strategy to fit the ESR model. In the first step, we model farmers' technology adoption decisions using the probit model to generate inverse Mills ratios while accounting for the unobserved heterogeneity (Alene and Manyong, 2007). The relationship that we consider in examining the impact of adoption on the productivity and income assumes a linear function of a vector of explanatory variables, X_i and an adoption dummy variable, A_i. Estimates α_r then represent a model for discrete X_i given as:

$$Y_i = d_{iX} X \beta_X + \alpha_r A_i + \mu_i \qquad (2)$$

Where Y_i is the dependent variable (mean of the outcome indicators); β_X is the regression induced effect when $X_i = X$; α_r is the regression parameter; A_i is a dummy variable for the use of the new technology such that $A_i = 1$ if the technology is adopted and $A_i = 0$ when the technology is not adopted and μ_i is a normal random disturbance term. Whether farmers adopt the technology or not is dependent upon the interaction of the characteristics of farmers and farms, hence the adoption decision for the technology package is determined by each farmer's self-selection and not random assignment.

The subsequent outcome equations are then estimated in the second step by factoring in the inverse Mills ratios as an additional regressor to capture selection bias. Following recommendations by Di Falco et al. (2011), we adopted the full

information maximum likelihood (FIML)[2] estimation method. This approach simultaneously estimates the probit criterion (selection equation) and the regression equations, thus yielding consistent standard errors. The outcome functions (yield/ha and income/ha) are estimated for adopters and non-adopters separately, thus taking into account the endogenous nature of adoption decisions. The relationship between the outcome variables and exogenous variables X_i for each possible regime is thus specified by the following equations:

$$A_i = 1 \ (z_i \gamma + u_i > 0), \qquad (3)$$

$$\text{Regime 1: } Y_{0i} = X_{0i} \beta_0 + \varepsilon_{0i} \ \text{ if } A_i = 0 (\text{no adoption}) \qquad (4)$$

$$\text{Regime 2: } Y_{1i} = X_{1i} \beta_1 + \varepsilon_{1i} \ \text{ if } A_i = 1 (\text{with adoption}) \qquad (5)$$

Where Equation (4) is the selection equation denoting the regime that applies, z_i is a $1 \times m$ vector of explanatory variables assumed to explain the adoption probability, and u_i, ε_{0i} and ε_{1i} are the error terms. As farmers' decision of adopting the blended pack can be endogenous, the correlation between error terms ε_{0i} and ε_{1i} based on the sample selection criteria has a non-zero expected value (Abdulai and Huffman, 2014). As such, the parameters (β_1 and β_2) of OLS estimation may produce sample selection bias[3]. Assuming that the three error terms, u_i, ε_{0i}, and ε_{1i}, have a trivariate normal distribution with a zero mean, then, the variance-covariance structure is:

$$cov(u_1, \varepsilon_{1i}, \varepsilon_{0i}) = \begin{bmatrix} \delta^2_u & \delta_{1u} & \delta^2_{0u} \\ \delta_{1u} & \delta^2_1 & \delta_{01} \\ \delta_{0u} & \delta_{01} & \delta^2_0 \end{bmatrix} \qquad (6)$$

Where δ^2_u, δ^2_1, and δ^2_0 are the variances of error terms u_i, ε_{1i}, and ε_{0i}, respectively; while δ_{1u} denotes the covariance of u_i and ε_{1i}; and δ_{0u} denotes the covariance of u_i and ε_{0i}. We also define the ρ as correlations between error terms, for farmers who adopted and those who did not adopt the technology, as $\rho_{1\mu} = corr(\varepsilon_{1i}, \mu_1)$ and $\rho_{0\mu} = corr(\varepsilon_{0i}, \mu_1)$. However, given the nature of the sampling, A_{i1} and A_{i0} do not occur at the same time, so the covariance between ε_{i1} and ε_{i0} is uncertain. Based on this assumption, the expected values of ε_{1i} and ε_{0i} can be used to account for the the inverse Mills ratio where $\lambda(\cdot)$ which is defined as:

$$\lambda_1 = \frac{\emptyset(z_i \gamma)}{f(z_i \gamma)} \ if \ (A_i = 1) \ and \ \lambda_0 = \frac{\emptyset(z_i \gamma)}{1 - f(z_i \gamma)} \ if \ (A_i = 0) \qquad (7)$$

Where $\emptyset$ and ϕ are the pdf and cdf of the standard normal variable, respectively. When $\rho_1 = \rho_0 = 0$ the endogenous switching regime model equations switch to the exogenous regime model. We recognize that there might be endogeneity of adoption in the outcome. This was partially addressed by including comprehensively selected covariates from literature

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[2]The FIML estimates of the parameters of the endogenous switching regression model were obtained using the movestay command in STATA.
[3]This is also known as the problem of missing variables (Lee, 1982).

(Zeng et al., 2015). Additionally, by having a valid instrumental variable that is exogenous, then λ_1 and λ_0 can be obtained from the first stage and included in regimes Equations (3) and (4) (Tufa et al., 2019). For identification purposes, our guiding hypothesis is that the probability of a household to adopt improved technology is an increasing function of its prior exposure reflected by the two selection instruments which are the soil fertility gradient and the storage[4]. Following Di Falco et al. (2011), we determine the acceptability of these instruments by conducting a rejection test of whether they affect the CSA technology adoption decision and not the income and productivity outcome variables among non-adopting households. Results show that the two variables can be considered as valid selection instruments.

In order to examine the effect of adoption on the productivity and income, we utilized the estimated coefficients from the ESR model to compute the average treatment effect (ATE). This defines the difference between the expected values of observed and counterfactual scenarios. In this study, we estimated the average treatment effect on the treated group (ATET) as the difference between Equations (7) and (8). ATET can be effectively used to eliminate the estimation bias caused by observed and unobserved factors and examine the overall effect of adopting the blended pack on farmers' productivity and income. In this regard, we also assume that $E\left(u^2_i\right) = 1$, and hence the conditional expectation of the outcome variable in Equations (3) and (4) can be defined respectively as:

$$E\left(Y_{1i}|x_i, A_i = 1\right) = x_i\beta_1 + \rho_1\lambda_1\left(z_i\gamma\right) \tag{8}$$

$$E\left(Y_{0i}|x_i, A_i = 1\right) = x_i\beta_0 + \rho_0\lambda_0\left(z_i\gamma\right) \tag{9}$$

Informed by Paudel et al. (2020) the ATET was calculated using Equation (9):

$$E(Y_{1i}|x_i, A_i = 1) - E\left(Y_{0i}|x_i, A_i = 1\right) = x_i\left(\beta_1 - \beta_0\right) + \rho_1\lambda_1 - \rho_0\lambda_0 \tag{10}$$

We then utilized the Nearest Neighborhood Method (NNM)[5] for mirroring experimental randomization and estimate the effects. In Equations (7–9), the term $E\left(Y_{0i}|x_i, A_i = 1\right)$ is the expected value of Y_i if the household had not adopted the CSA practice. It is the unobserved component which was estimated using counterfactual analysis as guided by Di Falco and Veronesi (2013). The term $E\left(Y_{1i}|x_i, A_i = 1\right)$ denotes the actual expected value of farmers' productivity and income.

RESULT AND DISCUSSIONS

This section presents the findings from the study and the discussion in relation to the existing body of knowledge on the adoption and impacts of agricultural technologies.

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[4]Two instrumental variables, soil fertility and storage were selected as guided by the socio-economic-institutional arrangements in the study area and applied across all the outcome models.
[5]A detailed explanation of the method is found in (Ali and Abdulai, 2010; Becerril and Abdulai, 2010; Amare et al., 2012). The Kernel Method has also been widely used in literature but was not adopted in the current study.

Descriptive Analysis

Table 2 shows the descriptive statistics for the sampled households and isolates some important indicators in terms of differences between the adopters and non-adopters.

It can be observed from the table that the farmers who adopted the technology for the 2020 cropping season had significantly higher yield per hectare and income per hectare by differences of 253.17 kg/ha and US$133.08/ha, respectively. The table shows that the average income per hectare for the whole sample is US$307.5/ha. The income per hectare are computed as the difference between the gross income from marketable yield (sales) after accounting for household consumption and the total costs of buying inputs (seed, fertilizers, chemicals), land preparation, weeding and harvesting. The opportunity cost of labor was adopted on the basis of the farm wage rates paid by farmers in the study area and the same approach was utilized for transport costs to and from the markets. The smallholder farmers have on average 4.3 ha of arable land which is characteristic of most farmers in the similar contexts in southern Africa.

A perception based measurement of soil fertility was adopted given that Tambo and Mockshell (2018), during a conservation agriculture study, reports the accuracy of farmers' characterization of the soils in their areas. The proportion of fertile soil was computed relative to the total arable land for the household and categorized as not fertile (0) and fertile (1). The variable was significantly higher for adopters (49%) as opposed to non-adopters (3%). The same was done for the availability of storage facilities at the farm which was also coded as, inadequate (0) and adequate (1) with response rates of 49.2 and 50%, respectively. This was important so as to get insights on the possible motivation to adopt the emerging CSA technology based on the potential of the soils and storage to generate income. The hypothesis was that farmers with more fertile land and storage facilities are more likely to adopt the emerging technology.

The dependency ratio had an average 35% and 33% for adopters and non-adopters, respectively. This variable was computed as the ratio of household members in the below 14 and above 65 years category relative to active household members in the 15–64 years range. Higher dependency ratios are usually an indicator of the need to adopt technologies and produce more to feed the dependents. For households with schooling, the total number of completed years in school was used to represent the education variable. Bahta et al. (2020) alluded to this when they noted that family composition has a direct bearing on technical efficiency gains as driven by sustainable agricultural management practices. The results in **Table 2** also show that the average duration in schooling of the respondents was 8 years and this was not significantly different across the adoption status. This reinforces observations by Bahta et al. (2018) who also noted homogeneity in the level of education among households in a home garden study in South Africa.

There were significantly more males in the non-adoption regime as was shown by the 15.2% difference relative to the female counterparts. Bahta et al. (2019) also noted a similar result when they recommended the need for women empowerment in as a strategy to reduce food insecurity. They argued that,

TABLE 2 | Description of variables included in the models and descriptive statistics.

Variable	Description	Unit of measurement	Total sample mean	Adopters mean	Non-adopters mean	Difference-test
Dependent						
Productivity	A continuous variable of sorghum produced per hectare during the season	kg/ha	902.726	944.344	691.167	−2.326**
Income	A continuous variable showing income per hectare of sorghum	US$	307.452	329.328	196.250	−2.973*
Independent						
Age	Continuous variable for age of household head	Years	44.721	45.713	44.252	−0.916
Arable land	Continuous variable for the total arable land for the household	Hectare	4.3153	4.1869	4.3759	1.478
Log costs	Continuous variable of logarithm of variable costs per hectare	US$	3.859	3.829	4.009	2.517***
Dependency	Continuous variable showing proportion of household dependent members	Percent	33.258	34.738	32.558	−1.083
Education	Continuous variable of the duration in schooling by the household head	Years	8.226	7.852	8.4031	1.253
Draft	Continuous variable shoeing number of effective draft animals available	Number	5.989	6.131	5.922	−0.5796
Experience	Continuous variable of cumulative experience years in sorghum production	Years	7.679	8.909	7.097	−2.078**
Aid value	Continuous variable for the value of sorghum aid received during the season	US$	8.597	14.795	5.667	−4.383*
Associations	Continuous variable for number of social groupings for household members	Number	1.697	1.574	1.756	1.441
Distance	Continuous variable for distance to the market in kilometers	Minutes	73.647	73.525	73.705	0.019
Payment time	Continuous variable of time between finalizing a transaction and payment	Days	11.297	11.639	11.136	−0.220
Gender	Dummy variable for gender of household head (0=female, 1=male)	Dummy	0.718	0.615	0.767	2.345**
Instrumental						
Soil fertility	Dummy variable for perceived soil fertility (0=not fertile, 1=fertile)	Dummy	0.4947	0.4868	0.2872	−2.279**
Storage	Dummy variable of storage facilities adequacy (0=inadequate, 1=adequate)	Dummy	0.4955	0.500	0.492	−0.236

Source: Authors' own computation.

*; ** and *** indicate p-values significant at 1, 5, and 10% levels, respectively; t-test was used for continuous variables and chi-square for categorical variable.

this could be effectively achieved when policy interventions take center stage. A similar approach can be adopted to support gender inclusive CSA adoption pathways. **Table 2** also highlights that there were no differences in the level of farming experiences but differences in the sorghum production experiences for the adopting and non-adopting farming households in the study area. However, similar studies show the likelihood of adopters to have more experience in both the general agricultural practices and specifically sorghum production. The diversity of livelihood sources has a bearing on how the decision to adopt emerging technologies will be made. In the study, the adopters had significantly higher income diversity and crop diversity as shown by the indices computed for the two clusters in **Table 2**.

Results also show that the adopters of the blended seed-fertilizer technology fetch higher prices (US$40.13) in the markets relative to the non-adopting counterparts (US$33.61). The variability in the prices can be attributed to the pricing adopted by buyers who highly grade the produce from adopters based on a preconceived perception that they produce higher quality grain. Some of the buyers are also contracted to processors who are willing to pay higher prices for the organically produced sorghum grain. In the same way, they also interact with more buyers (∼4.0) in the markets as opposed to the non-adopting farmers (∼3.0). This can be explained by the motivation to search for buyers in more rewarding markets for the higher outputs produced at the farms. These wider interactions also create awareness among the producers on the prevailing market prices, thus enhances their negotiating leverage. And with no immediate alternative for the preferred organically produced grain, the buyers end up offering higher prices in the markets. The finding supports findings by Bahta and Enoch (2019) who also reported a similar pattern in a study which recommended the use of policy interventions among vegetable farmers in South Africa. The results in **Table 2** also show no differences in

TABLE 3 | Full information maximum likelihood estimates of productivity and income.

| | Blended CSA adoption | Yield/ha | | Blended CSA adoption | Income/ha | |
| | | Adopters | Non-adopters | | Adopters | Non-adopters |
Variable	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
Arable land	1.046* (0.608)	2.150*** (0.749)	−3.411 (2.196)	0.014* (0.004)	0.35* (0.019)	−0.49* (0.023)
Log costs	−0.03* (0.008)	−0.242***(0.037)	0.193*** (0.0345)	−2.080* (0.677)	−0.248* (0.131)	0.057 (0.064)
Age	0.02 (0.012)	−0.67 (3.061)	−0.150 (0.1049)	−0.031 (0.013)	0.07 (0.617)	−0.177 (0.107)
Dependency	−0.01 (0.007)	−0.98 (2.001)	−0.221** (0.091)	0.022*** (0.008)	0.52 (0.405)	0.96 (0.779)
Education	−0.06 (0.046)	0.107* (0.049)	−0.322 (0.225)	−0.054 (0.047)	−0.876** (0.279)	−2.74 (3.683)
Draft	0.13** (0.059)	0.347 (0.273)	−0.034*** (0.010)	0.123*** (0.064)	1.24 (2.656)	−0.363* (0.098)
Gender	−0.41 (0.346)	−0.726 (0.503)	0.033 (0.048)	−0.642 (0.399)	−0.474 (0.321)	−0.2714 (0.2501)
Experience	−0.69 (0.279)	2.291*** (0.3632)	−0.225 (0.243)	0.332*** (0.089)	−0.158 (0.104)	0.17 (0.980)
Aid value	0.01 (0.008)	−1.876** (0.648)	−1.38** (6.552)	0.031 (0.008)	−0.934** (0.281)	0.65 (0.754)
Associations	0.24*** (0.140)	0.156** (0.064)	−0.037 (0.0319)	−0.423* (0.161)	−0.145 (0.106)	−0.555** (0.208)
Distance	0.03 (0.004)	0.51 (0.549)	−3.52 (3.268)	0.014*** (0.006)	0.246** (0.111)	1.12* (0.367)
Payment time	−0.555** (0.124)	−1.12 (2.508)	−3.212** (1.004)	−0.013 (0.020)	−0.19 (0.509)	3.31** (1.395)
Soil fertility	−1.40** (0.585)			−1.151** (0.339)		
Storage	−0.699** (0.279)			−1.194*** (0.349)		
Constant	6.69** (2.750)	−0.717*** (0.278)	−1.153*** (0.327)	0.992*** (0.3434)	4.69*** (0.4745)	2.56*** (0.4352)
rho0	−0.514 (0.1566)			−0.552 (0.1680)		
rho1	−0.1654 (0.2181)			− 0.187 (0.2736)		
/lns0	0.135*** (0.044)			3.744*** (0.2098)		
/lns1	0.593*** (0.064)			4.461*** (0.0828)		
/r0	0.568** (0.213)			0.979** (0.4481)		
/r1	0.167 (0.224)			0.349 (0.7052)		
Wald chi2 (12)	69.26***			64.23***		
Log likelihood	−495.711			−514.601		
LR test of indep. Eqns.	9.12**			7.16**		
No. of obs.	380			380		

Source: Authors' own computation.

*; ** and *** indicate p-values significant at 1, 5, and 10% levels, respectively; z-values estimated on robust standard errors in parenthesis.

variables such as payment time, which shows the time between a transaction and the point of payment, the distance to the markets and the associations. In as much as there are some indicators of differences across variables, this cannot be objectively used in decision making since these are isolated summaries. Modeling the impact of the adoption decision using ESR can therefore be useful in informing the decisions while guided by the empirical evidence from the mid-Zambezi valley of Zimbabwe.

Empirical Results

The empirical analyses were done using STATA 15 statistical package where the adoption and outcome (yield/ha and income/ha) equations are jointly estimated using full information maximum likelihood approach. **Table 3**[6] shows results of the ESR with the selection equation and the equations for the two regimes (Equations 3, 4) as explained in earlier sections. The

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[6]The variables, sigma, /lns1, lns2, /r1, and /r2, are ancillary parameters used in the MLE procedure. Sigma1 and Sigma 2 are the square roots of the variances of the residuals of the regression part of the model and lnsig is its log. r1 and r2 are the transformation of the correlation between the errors from the two equations (Lokshin and Sajaia, 2004).

selection equation is shown in the first columns and results are explained as the normal probit model. We included the categorized percentage of fertile land available for the farmer (soil fertility) and adequacy of storage facilities as valid instrumental variables in the selection equation to assure identification (Lee, 1982; Ngeno, 2017).

The instruments, while they are uncorrelated with the two dependant variables (selected outcome indicators of income/ha and yield/ha), they are also highly significant ($p < 0.01$) in both selection models and hence we conclude that they are valid. A strong negative co-relationship with the adoption decision shows that farmers who have higher proportions of fertile land are less likely to adopt the CSA practice of using emerging varieties and inorganic fertilizers. This may be because there is more competition for fertile land with other major crops such as maize which is highly supported by the government and its agents (Sinyolo, 2020). Farmers with adequate storage facilities are also more likely to adopt the technology in anticipation of incurring less post-harvest losses after generating higher yields. This offers opportunities for tapping into market windows during the lean season phases and

fetch higher prices since commodities will be in shortage and prices more favorable.

Based on the selection criterion shown in the first column of **Table 3**, the most important factors affecting the adoption of the blended seed-organic fertilizer technology as a CSA strategy at the household level are arable land, variable costs, dependency ratio, education, availability of draft power, experience in sorghum production, value of aid, associations, distance to the market, payment time. The availability of more arable land has the propensity to significantly ($p < 0.1$). This can be explained by the patterns where the available land facilitates access to space to try out new technologies without compromising the farmer's land allocation plan, thus reducing the exposure to possible failure of the technology. Bale et al. (2013) concurs with this viewpoint and noted that, reduction in risks of crop failure is also another benefit which emanates from the availability of land where diversity in crop production helps to spread the risk tendencies. This is a fundamental outcome since there is scope for land reallocation among smallholder farmers toward the intensive producers from a policy perspective to target the production of sorghum, especially given the nature of land rights in these communities.

Associations to which household members belong has a positive bearing on the CSA adoption decision as shown in **Table 3**. This is because of the ability of networking arrangements to take place and information on the costs and benefits of these technologies discussed. The result support findings by Mutenje et al. (2016), Mapfumo (2017), and Baiyegunhi et al. (2022) who alluded that associations are hubs of information which may be critical in exposing farmers to new production systems and viable markets thereby catalyzing adoption prospects. Nciizah et al. (2021) showed that understanding this can facilitate the design of climate change adaptation strategies in the drylands of Zimbabwe. The results also show that availability of effective draft power has a positive and significant effect on the adoption decision. As such, rational farmers who have access to reliable draft power are more likely to adopt emerging productivity enhancing technologies. The variable assures timely land preparation which also plays an integral role in enhancing the performance of agricultural activities especially in the drylands where rainfall unpredictability is higher. In conservation agriculture studies by Nyanga (2012) and Abdulai (2016), similar observations were made where the multi-purpose uses of draft power in rural farming communities of southern Africa, such as for transporting inputs from markets and produce to the markets also played a part in the adoption decision. Tapping into this variable from a policy angle, as alluded to by Smale et al. (2018) can be done through livestock revolving schemes in the drylands with the aim of boosting the livestock herd and grease the production of sorghum.

In the selection model, as the variable costs increase, the likelihood of adopting emerging CSA technologies are observed to decline. This may be because, farmers who experience higher variable costs of production tend to shun these emerging technologies and possibly opt for alternative practices which are more cost effective. This is particularly so since variable costs will increase as the scale of production increases, thus crowding out prospects of adoption as driven by additional increases in land allocated toward the crop will also pull with it the variable costs structure and reduce the margins. This finding corroborates the study by Martey et al. (2021) who reported that, in farming systems, production costs are also directly related to the net benefits and need to be managed at both the operational and policy levels Makindara et al. (2013) weighs in and suggest that market mechanisms need to be readjusted to accommodate these peripheral crops if high value chains such as the clear beer chain are to generate value for stakeholders. These are critical insights into how the reduction of production costs can drive income levels up.

The dependency ratio has a positive and significant effect on the decision to adopt the blended CSA practice by the farmer. Households with larger dependency bases are more likely to be willing to experiment with emerging technologies with the hoping of getting higher yields for food and income needs. This is consistent with the findings and reasons of Ng'ombe et al. (2017) who reported the higher incidences on families with dependent members being more involved in conservation farming and getting higher revenues in the process. This isolates the need for oriented policies which aim to cushion the farmers with larger dependency ratios through for example proportional explicit subsidies. Payment time is reported to have a negative and significant effect on the farmer's proclivity to adopt the blended CSA technology. If the target crops' marketing arrangements are open to delayed payments in existing markets, then farmers will not be motivated to adopt the technology regardless of the other benefits such as yield and income gains. This is supported by Suresh et al. (2021) when they observed that some climate change adaptation strategies were less adopted because the output from their systems had challenges with payment arrangements for supply delivered to the markets. Thus, should motivate strategies which target price efficiency in agricultural market through moral suasion of legal proclamations.

The results for the two regime equations of adoption and non-adoption are shown in the second and third columns of **Table 3**. Variable costs emerge as a highly important determinant in both regimes for the yield per hectare cultivated. The same can be said for the arable land variable in relation to income per hectare cultivated. However, the income effect is relatively higher (0.49) for non-adopters as compared to the adopters (0.35). Sinyolo (2020) postulates that, as a way of looking into the future, this might act as a disincentive for the present non-adopters to migrate into the adoption cluster as they will lose a net benefit in the process. However, the variable cost structure shows that as the variable increases, then the income for the non-adopters decrease at a steeper rate relative to the yield gains. As such, assuming favorable output market prices, as currently offered by the government as an additional support package, the net effect based decision from yield and variable cost will be for farmers to adopt the emerging CSA technologies.

The results also show that for the two regimes, under income per hectare, the distance to the markets, value of aid, experience

TABLE 4 | Average treatment effect of adoption on productivity and household income.

Index	Productivity (kg/ha)			Income ($/ha)		
	Estimate	AI Robust Std. Err.	z value	Estimate	AI Robust Std. Err.	z value
ATT	243.598	124.081	1.80*	99.893	55.499	1.96**
ATU	−232.125	108.5782	2.14**	−58.958	28.663	2.06**
ATE	241.712	121.525	1.99**	93.164	50.455	1.85*

Source: Authors' own computations.
* and ** indicate p-values significant at 1 and 5% levels, respectively.

and education are important determinants. As opposed to aprior expectations, when the distance to the market increases, the income also increases. This can be attributed to the observations from the study area which showed that distant markets are the ones which offer higher prices. As such the observed model outcome is in tandem with these observations while defying the existing hypothesis of a negative relationship between distance to the markets and income. Evidence from similar previous studies also report patterns in which experience with local markets show that they are not as lucrative as external markets (e.g., Martey et al., 2021). Decentralization of these markets can help to reduce the distance between buyers and sellers. Alternatively, the sorghum value chain actors may also invest in digital marketing alternatives. Thus, reaching out to a wider range of clients. The value of aid is also reported as an important factor when outcomes about possible gains in yield and income are made. Access to aid packages will reduce the burden of searching for and accessing inputs, thus reduces the transaction costs (Maina et al., 2015). These costs are reported by Hamukwala et al. (2010) need to be managed even from external to the farmer's plot so as to boast productivity and income.

The payment time is a significant consideration for non-adopters in both the productivity and income clusters. However, the direction of effect for the two regimes is different, and it is positive in the former and negative in the latter outcome. The variable is however insignificant in the adopters' decisions in contrast to findings by Suresh et al. (2021) who reported higher income for farmers who were paid at a later stage. This can be attributed to the likelihood that, the payment time as well as the modes used are not considerably different among the respondents in these clusters.

The treatment effects estimates for the adoption of blended seed-fertilizer technology on productivity and household income are reported in **Table 4**.

The Average Treatment Effect on the Treated (ATT) is a measure of the difference between the productivity and household income of the adopting units and the values, they had not adopted the blended CSA. Results of the ATT shows that the productivity for the treated group of farmers is positive (243.598) and statistically significant. The same can be said for the household income which is positive (99.893) and statistically significant. This implies that, the blended CSA adopting households would have been worse off in terms of income and productivity had they decided not to adopt the blended CSA package. The adoption effect of the technology on farmer's income/ha and yield/ha is approximately a 30.3 and

25.8% increase, respectively. Similarly, results from **Table 4** show that, using the Average Treatment Effect (ATE) outcomes, as derived from ESR, the non-adopting households would have attained income and productivity gains had they adopted the blended CSA technologies. The Average Treatment Effect on the Untreated (ATU), measures the difference between the productivity and household income of the non-adopters and the associated counterfactuals. The estimates account for the selection bias, in contrast to the mean differences reported in **Table 2**. Results show that, the ATU is negative for both productivity and household income with values of −232.12 and −58.96, respectively. These findings reveal that adopters of the blended CSA package would have been worse off, in both productivity and income terms, had they opted not to adopt the package, while the non-adopters would have also benefited if they had opted for the adoption pathway.

The findings, as highlighted in **Table 4** show that, the adoption of blended improved sorghum seed and partial-organic fertilizer CSA technology has a significant effect on both the productivity and household income of the adopting households. This result concurs with other studies, which also reported the gains from adoption of the different dimensions of CSA adoption (Musara and Musemwa, 2020; Mujeyi et al., 2021). As reported by Ghimire and Huang (2015) in Nepal, farmers who adopted improved maize varieties generated household wealth as opposed to the non-adopting counterparts. A study by Mujeyi et al. (2021) on the impact of CSA on household welfare in smallholder integrated crop–livestock farming systems also confirmed a robust relationship between food security, income and CSA adoption. It therefore shows that, the CSA interventions implemented in the smallholder farming societies have the potential to support gains among the adopting households in various dimensions including productivity and income. Assuming that the income/ha and yield/ha are the core desired objective for the farmers, then adopting the blended improved sorghum seed and partial-organic fertilizer package technology will be more valuable as they are likely to gain from the adoption as compared to the state of non-adoption.

CONCLUSIONS AND IMPLICATIONS FOR POLICY

The study aim was to examine the impact of adopting farmer initiated emerging CSA practices in the form of a blended

improved sorghum seed variety and partial-organic fertilizer pack on productivity and net income among smallholder households in the drylands of Zimbabwe. Based on results from an ESR model, it can be concluded that, a combination of farm specific factors (arable land, variable costs) and external factors (distance to the market, value of aid) have a bearing on the adoption decision and the associated impact on productivity and income for the reviewed technology. This intricate matrix of determinants shows the crosscutting nature of these driving factors and as such the associated complexity of managing technologies through the adoption and impact management lens. Based on the average treatment analysis, it can also be reported that farmers who decide to adopt the CSA pack are relatively better off in terms of productivity and income and thus offering an incentive for adoption beyond the current coverage. In light of the conclusions, the starting point of intervention should center on multi-dimensional infrastructural development initiatives such as seed banks, information hubs and storage facilities which unlock the avenues for smallholder farmers in marginalized drylands to interact efficiently and effectively with link-agents of emerging technologies. The results could be more generalizable if study focused on a national level scale of the analysis while using a multinomial ESR for analysis. To support this, additional research can also be done on the human capital development options and how they affect the Indigenous Technical Knowledge (ITK) based entrepreneurial capabilities of the smallholder farmers in the framework of scaling out the technology.

DATA AVAILABILITY STATEMENT

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

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by Bindura University of Science Education Research and Ethics Committee. Written informed consent for participation was not required for this study in accordance with the national legislation and the institutional requirements.

AUTHOR CONTRIBUTIONS

JMu and LM designed the research protocols. JMu provided the data. YB, JMu, and JMa analyzed the data and prepared the manuscript with contributions from all co-authors. YB, JMa, and LM proofread the manuscript and made suggestions for corrections. All authors read and approved the final manuscript.

FUNDING

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