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Impact of adoption of conservation agriculture on farm productivity and financial performance in Tanzania

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Abstract

Conservation agriculture (CA) has gained momentum in recent years in response to growing threats to human livelihoods and the environment from anthropogenic activities such as unsustainable farming practices, excessive use of chemical fertilisers, deforestation, urbanisation and greenhouse gas (GHG) emissions. These factors collectively drive climate change, the decline in soil fertility and reduced crop yields, undermining food security and farmer incomes. The cycle perpetuates persistent food insecurity and poverty, particularly in agrarian economies. Conventional agricultural systems are increasingly unable to meet these challenges, prompting a shift toward sustainable CA. However, limited evidence exists for how the intensification of CA affects both crop and financial performance. Using nationally representative cross-sectional data, the study investigated the impact of CA adoption through a multivalued treatment framework. Doubly robust augmented inverse probability weighting (AIPW) and inverse-probability-weighted regression adjustment (IPWRA) estimators were adopted to assess gross yields, productivity, costs, profits and returns on investment. The findings, which could withstand a series of robustness checks, show that greater CA intensification yields higher rewards for farmers. However, these benefits come with additional costs that influence profits and returns on investment. The results suggest that stakeholders should look beyond yield improvements alone and consider the associated costs to fully capture CA's profitability. Policies promoting CA adoption should therefore emphasise optimal combinations of CA technologies that maximise returns, while minimising costs.

Key words: Tanzania, conservation agriculture intensification, smallholder farmers, financial performance, impact, gains, IPWRA

1. Introduction

Conservation agriculture (CA) was pioneered by the Food and Agriculture Organization (FAO) in 2011 and defined as a set of farm-level practices reflecting the following core interrelated areas: a) minimal soil disturbance (the technologies include minimum tillage or zero tillage, b) preserving everlasting soil cover (the practices include intercrops, mulching, agroforestry, row planting, fertiliser application, improved seeds, crop residue management, integrated pest management (IPM) and agro-ecology, and c) crop rotation/diversification (the embedded technologies include crop rotations) (Kuntashula *et al*. 2014; Binam *et al*. 2015; Bhatt 2017; Coulibaly *et al*. 2017; Mkonda & He 2017; Nyasimi *et al*. 2017; Sims & Kienzle 2017; Kassam *et al*. 2018; Li *et al*. 2019; Shakoor *et al*. 2021; Nyathi *et al*. 2022; Bongole 2023; Ngaiwi *et al*. 2023; Tadesse & Ahmed 2023; Thierfelder & Mhlanga 2022; Eke Balla 2024; Erekalo *et al*. 2024; Omulo *et al*. 2024; Ruiz-Espinosa *et al*. 2024).

The full adoption of CA requires that all triple key principles are practised in a farming system (Ngaiwi *et al*. 2023). The adoption of CA is advocated globally, especially in the sub-Saharan Africa (SSA) and Asia regions, which have a large farming population (Omulo *et al*. 2024). There has been an upward scale-up of CA application in SSA in recent years, with an increase of 211% from 2009 to 2018.

Furthermore, about 1% of global arable land is under CA, and 1.1% of African’s arable land is under CA (Kassam *et al*. 2018). Under conditions of severe climate change impact, up to 85% of farmers have adopted conservation agriculture in specific locations in Tanzania (FAO 2005). However, at country level, about 36% of Tanzanian farmers have adopted conservation agriculture (The United Republic of Tanzania 2020).

There is low buy-in in CA intensification, regardless of the various initiatives used, such as promotions, training and research conducted by development partners, agencies, governments and researchers. Slow adoption can be explained by limited knowledge, credit shortages, partial adoption, overdependence on donor funding programmes, labour intensiveness, low initial yield and benefits, crop residue management struggles, location limitations, high farm input costs, social norms and values, limited capital, land tenure, weak technological advancement, limited access to extension officers and services and limited skilled labour, the fact that, without tillage, weeds increase, and limited access to farm inputs (Mkonda & He 2017; Holden *et al*. 2018; Kassam *et al*. 2018; Thierfelder & Mhlanga 2022; Omulo *et al*. 2024).

The hurdles have made the intensification of CA adoption exhibit temporal and spatial variation (Mkonda & He 2017) and farmers respond to climate change threats based on their local knowledge and resources (Kassam *et al*. 2018). For instance, CA practices based on indigenous knowledge, such as *terraces*, closed range (*ngitiri*), *planting basins*, cover crops (*lablab*), *Matengo* and *chololo pits*, are predominant in Tanzanian farming systems (Mkonda & He 2017).

Many places in Tanzania face droughts, floods and soil erosion as climate change impacts (United Republic of Tanzania [URT] 2015; Mugabe 2020; Ogada *et al*. 2020; Bongole 2022, 2023; World Bank Group 2024). In response, farmers adopt CA practices such as residue management, crop rotation, intercropping, minimum tillage and contours on their farms (The United Republic of Tanzania 2020).

The intensification of CA adoption is suitable in farming and has become a key component of climate-smart agriculture (CSA) (Abdulai 2016; Holden *et al*. 2018; Jayne & Sanchez 2021; Omulo *et al*. 2024; Ruiz-Espinosa *et al*. 2024). Integrating CA practices into farming results in positive feedback on soil quality, and eventually in positive impacts on soil management and crop production (Shakoor et al. 2022) in the long and short term (Thierfelder & Mhlanga 2022).

The growing strand of research on CA focuses on factors influencing the usage of particular CA technologies, barriers, challenges, problems, environmental benefits, and its effect on soil management and food security in a specific context (Mkonda & He, 2017; Kassam *et al*. 2018; Ngaiwi *et al*. 2023).

The impact of the intensification of CA adoption on farm and financial performance is rarely investigated. Furthermore, the extant studies present inconsistent views of the empirical relationship between the practices of CA and farm performance (Asante *et al*. 2024). There has been very little investigation of the impact of levels of CA adoption on increases in gross yields, and less attention is paid to outcomes such as operational expenses, profit gains and returns on investment.

This means that the impact of the intensification of CA adoption on farm and financial performance is underexplored, especially in Tanzania. This study was conducted to unveil the impact of the intensification of CA adoption on farm and financial gains. The study focused mainly on the question, 'what are the impacts of levels of CA adoption on farm and financial performance in Tanzania?'

The paper thus makes both academic and policy contributions, as follows: first, the study is novel in a Tanzania-specific context. The research enriches the extant literature for Tanzania, given its comprehension examination of the impact of the intensification of CA practices on selected outcomes. The paper serves as a reference for futures studies in this and related fields.

Second, the study provides insightful information to stakeholders on the formulation and reinforcement of CA practices as policy support measures. The study undertook a quasi-experimental analysis of the impact of intensification of CA on farm and financial performance. Feasible policy support is necessary to scale up the adoption of relevant soil management technologies for a sustainable environment and crop production, and the corresponding associated financial risks require a comprehensive understanding.

The remainder of the paper is organised as follows: Section 2 presents the literature review. Materials and methods are summarised in Section 3 and Section 4 depicts the empirical view and a discussion of the results, while Section 5 contains the conclusion and policy implications.

2. Literature review

2.1 Theoretical literature review

The theories that guide the study include utility and production theories. Utility theory reveals individuals' preferences. It is assumed to explain small farmers' behaviour in relation to farming decision-making (Akter et *al*. 2022). It claims that a choice is made based on maximum satisfactions attained from farming (Fishburn 1970). Farmer's satisfaction refers to the gains in terms of crops and finance from farming decisions.

Small farmers' choice to adopt CA is at a multivalued level. They may decide either to adopt to a low, moderate or higher extent. The decision is based on the satisfaction maximisation from the decision made about the adoption of CA technologies.

Let us assume the benefits of adopters is Y_{1i} in comparison with non-adopters, which is Y_{0i}. Small farmer i^{th} can opt to adopt a particular level of CA technologies if $Y_{1i} > Y_{0i}$ and the net gain is $U_{1i} > 0$. Despite the farmer's preference and CA adoption being clear to the farmer and the researcher, the net benefits accrued by the farmer are unobservable.

Thus,

$$U^*_{1i} = Y_{1i} - Y_{0i} > 0 \tag{1}$$

When a farmer makes a decision about the level of adoption and is satisfied, he or she will employ a certain combination of production inputs. The combination of factors of production is what we call the production function, which is explained by production theory.

Therefore, production theory describes crop productivity per hectare, given agricultural inputs and other factors (CA technologies) at a particular level of technology (Førsund *et al*. 1980; Missiame *et al*. 2021). It demonstrates the technical nexus between agricultural inputs and crop and financial gains, as well as their optimum at a fixed level of inputs (Farrell 1957; Lovell 1993), so that variables affecting crop productivity and finance are realised (Meeusen & Van den Broeck 1977).

We can state the production theory as a standard production function called Cobb-Douglas in its first-order condition, which can be expressed as

$$Y_{1i} = AL^{\alpha 1i} K^{\alpha 2i} Q^{\alpha 3i}, \tag{2}$$

where Y_{1i} is crop productivity per acre or farm financial gain, A is a constant term, L is labour employed (adult male and female farmers), K is capital (here of seeds, land, etc.), Q summarises the factors used in production (here of farm inputs, biophysical, socioeconomical and institutional), while $\alpha 1i$, $\alpha 2i$ and $\alpha 3i$ are estimated vector elasticities.

A smallholder farmer's satisfaction is a function of observable (farm inputs, socioeconomic, biophysical, and institutional) and unobservable (preference, inborn techniques, motivation, social network, management skills, experience, or risks) factors (Abdulai 2016; Amadu *et al*. 2020; Akter *et al*. 2022).

With respect to the effect and stress of climate change, farmers' agricultural production decisions are claimed to be dependent. We assume that farmers are risk neutral and insight into whether adopting CA improves crop and financial gains after selling crops forms the foundation of their decisions.

Furthermore, farmers who adopt CA improve nutrients and organic matter in their soil and prevent soil erosion (Jones *et al*. 2023), thereby augmenting crop productivity and financial gains after the sale of crops (Noltze *et al*. 2013; Akter *et al*. 2022).

The synthesis in the literature review enabled the construction of a conceptual framework (see Figure 1) and the hypothesis guiding the study.

H1: Adopters of higher CA intensification achieve higher crop and financial gains than non-adopters.

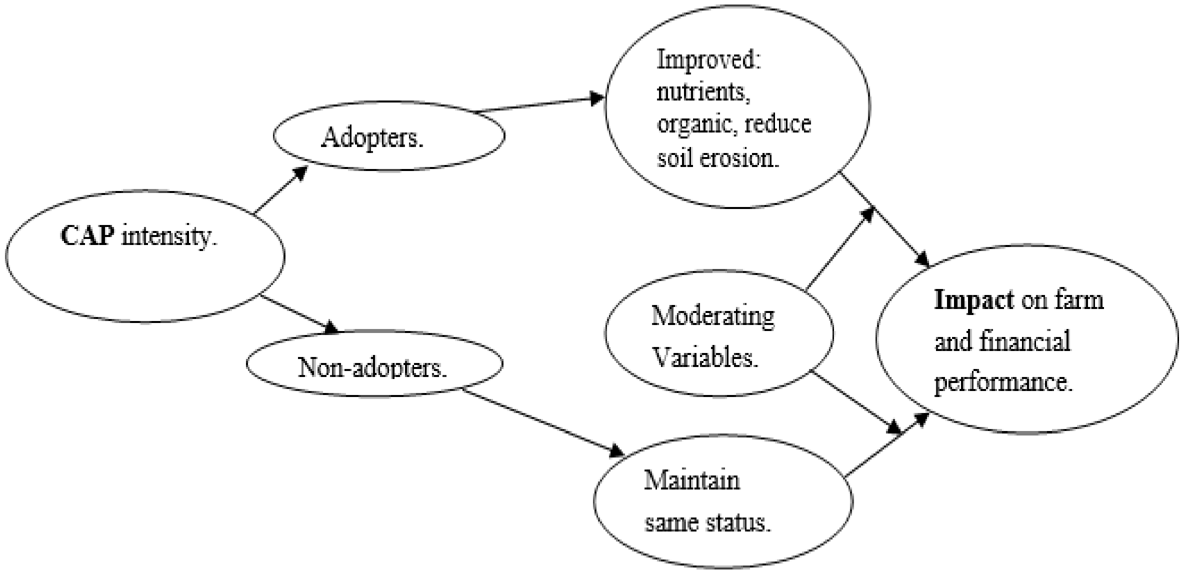

Figure 1: The conceptual framework
Source: Own work

2.2 Empirical literature review

The CA practices have been well researched, and have both socio-economic and environmental benefits. Nevertheless, some research findings claim that the adoption of CA and relative gains depict spatial and temporal variations (Mkonda & He 2017; Ngaiwi *et al*. 2023). Several studies on CA examine the nexus between CA adoption and the production of food crops (Chen *et al*. 2019; Li *et al*. 2019; Boufous *et al*. 2023).

For instance, some extant studies have examined the determinants of CA usage and found that factors such as socioeconomic, government policy (subsidies, inputs), social and psychological, biological, cultural, institutional and ecological drive the practices and CA adoption (Shakoor *et al*. 2021; Boufous *et al*. 2023; Awah Manga *et al*. 2024; Ngoma *et al*. 2024).

There further are studies that examine technology diffusion and the intensity of CA adoption (Mkonda & He 2017; Ngaiwi *et al*. 2023). Some focus on factors affecting the acceptance of a certain CA technology among smallholder farmers (Rezaei *et al*. 2020), while others assess the association between CA and food security (Manda & Alene 2018).

The extant literature shows that one strand of studies focused on the effect of the control of GHG emissions from agricultural activities on soil management and its ability to improve crop yields (Shakoor *et al*. 2021, 2022). However, some CA impact assessments elucidate that the adoption of CA may result in lowering the harvest, especially in the early stages of adoption (Simutowe *et al*. 2024; Sun *et al*. 2024; Sahay *et al*. 2025; Yemadje *et al*. 2025). These recent studies have begun to provide insight into how CA adoption may lead to either a negative or positive nexus between adoption and small-scale farmers' farm and financial performance.

The limitations of the existing studies include focusing only on determinants, challenges, opportunities, food security, reduction of GHG and soil management. There seldom is a discussion of the assessment of the impact of the intensification of CA on farm and financial performance. This means that researchers currently know relatively little about the impact of CA intensification on smallholder farmers' farm and financial performance.

If stakeholders want a better understanding of the impact of different levels of CA adoption on farm and financial performance, then conducting impact assessments on how smallholder farmers successfully benefit from CA adoption is critical. This study uniquely investigates how the levels of intensity of CA adoption improve farm and financial performance. It does so by using doubly robust augmented inverse probability weighting (AIPW) and inverse probability-weighted regression adjustment (IPWRA) estimators.

The findings of this study contribute to an understanding of whether smallholder farmers gain according to the levels of intensity of CA adoption. It will also contribute to realising the financial implications for farmers of their farm investment that corresponds to the extent of adoption and the associated costs. Policy makers will be able to use the findings to reinforce specific strategies and patterns of CA adoption for a successful cost-benefit trade-off.

3. Materials and methods

3.1 Data source

This study uses secondary data from the National Sample Census of Agriculture (NSCA) of Tanzania of 2020 (The United Republic of Tanzania 2020). The sampling procedure involved two stages. First, the survey identified both rural and urban enumerated areas (EAs) as primary sampling units (PSUs). It sorted the regions and districts according to probability proportionate to size (PPS). The second stage involved selecting agricultural farming households from the EAs for data collection.

The probability of a household being interviewed depended on the number of households in a particular EA. Households were selected randomly. Data was collected using structured questionnaires. To avoid bias in the farmers' recalling of the data, the survey was conducted immediately after the farming season. We also report financial information about income and off-farm income. This was obtained by observing and recording the harvests in terms of kilograms and recording the harvest values as reflecting the prevailing market price.

The study used a sample of 1 009 smallholder farmers after cleaning to meet the international standard that smallholder farmers are those who cultivate less than two hectares (Noltze *et al*. 2013; Rapsomanikis 2015; Tanzania National Council for Financial Inclusion [TNCFI] 2017; Acclassato *et al*. 2021). During the survey, these farmers reported experiencing climate change impacts, be it drought, soil erosion or floods, in the preceding three years. About 524 farmers adopted conservation agriculture as a response to the impact of climate change, and 485 farmers did not adopt.

The adopters practised CA technologies such as contours, planting legumes, using organic fertilisers, covering soil and fallowing (The United Republic of Tanzania 2020). Accordingly, the adopters were categorised into three levels of CA adoption intensity – low CA adopters, moderate CA adopters and high CA adopters. Adopters in the low category comprised smallholder farmers who adopted two or fewer CA technologies. The moderate category included farmers who combined three CA technologies, while, in the high category, at least four CA technologies were combined.

3.2 Description of variables

The variables in this paper are consistent with those in existing studies (Cattaneo *et al*. 2013; Binam *et al*. 2015; Linden *et al*. 2016; Ma *et al*. 2018; Smale *et al*. 2018; Asante *et al*. 2024). Smallholder farmers' CA adoption status (treatment variable) is categorical, where 1 represents low adopters, 2 shows moderate adopters and 3 indicates high CA intensity adopters (Ngaiwi *et al*. 2023).

The outcome variables include gross maize yields, average maize production, variable costs, profits and return on investment (RoI), as described in Table 1. The predictors are selected to match the untreated plots with treated plots with respect to data. We believe that our multivalued treatment effects framework addresses only the selection bias that might be emanating from observable predictors.

Specifically, we included a vast set of control variables, from farm inputs, biophysical and socioeconomic to institutional variables. Just as in many other places, farmers depend on conducive climatic conditions such as temperature, rain, humidity and precipitation (Ma *et al*. 2018). We further included dummy variables to control for location effects on outcomes. We included in the model the climatic regions of Tanzania (here of humid, tropical cool, tropical warm and semiarid). The summary of the statistics and descriptions of the variables are reported in Table 1.

Table 1: Definitions of variables and summary of statistics for the adopters

Variable	Description	Mean	Std dev.
Treatment variable			
Intensity of CA adoption	1 = low-, 2 = moderate- and 3 = high-intensity CA adoption	1.268	.565
Outcome variables			
Maize yield	Gross harvest in kg	5.507	1.867
Maize productivity	Gross harvest in kg /hectare	5.968	1.946
Variable costs	Operating expenditure per hectare in Tanzanian shillings (TZs)	9.857	2.914
Profits	Total revenue minus total cost incurred in TZs	11.891	1.107
RoI	A ratio of the profits to the variable costs in TZs	1.224	1.703
Covariates			
Age	Age of a farmer (years)	48.918	14.804
Gender	1 if a farmer is male, 0 otherwise	0.71	0.454
General education	1 if a farmer has formal education, 0 otherwise	0.197	0.398
No formal education	1 if a farmer has no formal education, 0 otherwise	0.191	0.393
Household size	Number of family members (persons)	5.023	2.404
Access to agricultural credit	1 if a farmer accessed agricultural credit, 0 otherwise.	0.057	0.233
Member of cooperative	1 if a farmer is a member of a farmers' cooperative, 0 otherwise	0.055	0.229
Member of an organisation	1 if a farmer is a member of a farmers' organisation, 0 otherwise	0.071	0.256
Access to extension services	1 if a farmer accessed extension services, 0 otherwise	0.13	0.336
Distance to the market	Distance to the nearest market in km	11.158	10.236
Distance to the plot/farm	Distance to the plot/farm in km	4.538	2.651
Off-farm income	1 if the farmer has another income-generating job, 0 otherwise	0.433	0.496
Farm size	Plot size in hectares (planted maize)	1.082	0.613
Irrigation	1 if the farmer used irrigation on the plot/farm, 0 otherwise	0.107	0.309
Used tractor	1 if the farmer used a tractor on the plot/farm, 0 otherwise	0.372	0.484
Improved seeds	1 if the farmer used improved seeds on the plot/farm, 0 otherwise	0.176	0.381
Information source channels	1 if the farmer used a radio, phones or the internet to acquire agricultural information, 0 otherwise	0.145	0.352
Past drought	1 if the farmer experienced drought, 0 otherwise	0.472	0.5
Humid	1 if the farmer is located in humid regions, 0 otherwise	0.065	0.247
Tropical cool	1 if the farmer resides in tropical cool regions, 0 otherwise	0.468	0.499
Tropical warm	1 if the farmer resides in tropical warm regions, 0 otherwise	0.305	0.461
Semiarid	1 if the farmer is located in semiarid regions, 0 otherwise	0.135	0.343

Source: The United Republic of Tanzania (2020)

Table 2 contains the mean and pairwise mean differences of the outcomes for the pooled sample (adopters and non-adopters) and the sub-samples of the adopters. The analysis indicates that there are significant differences between outcomes and levels of intensity of adoption of CA characteristics.

The differences give insights into the presence of potential systematic self-selection between the adopters and non-adopters. The details are presented in the discussion of the model specification and how it is addressed (see section 3.3).

Table 2. Means and pairwise mean differences in characteristics between CA adopters

Variable	Mean of CA adoption intensity			Mean differences			
	Low	Moderate	High	Pooled sample (A&N)	M&L	H&L	H&M
Treatment variable							
Intensity of CA adoption	1	2	3				
Outcome variables							
Maize yields	5.549	5.72	5.537	0.393***	141.332	-0.012	-0.183
Maize productivity	6	6.143	5.611	0.364	0.143	-0.389	-0.532
Variable costs	9.94	10.675	10.42	0.253	0.735*	0.48	-0.256
Profits	11.809	12.13	11.931	0.566*	0.316	-1.026	-1.342
RoI	1.106	1.334	0.353	0.126	0.229	-0.753*	-0.981*
Covariates							
Age	49.309	49.96	54.952	-0.181	0.651	5.644	4.992
Gender	0.75	0.72	0.81	0.036	-0.03	0.06	0.089
General education	0.202	0.26	0.286	0.007	0.058	0.084	0.026
No formal education	0.206	0.08	0.143	-0.067*	-0.126**	-0.063	0.063
Household size	5.055	5.42	4.905	0.236	0.365	-0.15	-0.515
Access to agricultural credit	0.059	0.08	0.048	-0.003	0.021	-0.011	-0.033
Member of cooperative	0.051	0.1	0.095	0.025*	0.049	0.044	-0.005
Member of an organisation	0.074	0.1	0.048	0.042***	0.026	-0.026	-0.052
Access to extension services	0.14	0.16	0.333	0.056***	0.021	0.194	0.174
Distance to the market	11.39	8.68	9.095	0.49	-2.71*	-2.295	0.415
Distance to the plot/farm	4.562	4.46	4.571	-0.305*	-0.103	0.009	0.112
Off-farm income	0.426	0.42	0.571	0.037	-0.007	0.145	0.151
Farm/plot size	1.077	1.128	1.351	-0.04	0.052	0.275*	0.223
Irrigation	0.129	0.1	0.143	0.045**	-0.029	0.014	0.043
Used tractor	0.342	0.34	0.286	-0.046	-0.002	-0.056	-0.054
Improved seeds	0.18	0.14	0.19	0.003	-0.04	0.011	0.051
Information source channels	0.147	0.22	0.286	0.048**	0.073	0.139*	0.066
Past drought	0.437	0.36	0.333	-0.068**	-0.077	-0.104	-0.026
Humid	0.059	0.08	0.143	0.046***	0.021	0.084	0.063
Tropical cool	0.463	0.38	0.571	-0.021	-0.083	0.108	0.192
Tropical warm	0.335	0.34	0.19	-0.056*	0.005	-0.144	-0.149
Semiarid	0.099	0.18	0.048	0.029	0.081	-0.052	-0.133
Sample size	272	50	21	1 009	332	293	71

Note: *, ** and *** represent significance of the 10%, 5% and 1% levels, respectively.
The pooled sample includes both adopters and non-adopters (A & N) of CA, which adds up to 1 009 small-scale farmers. Other column comparisons are based only on the sub-sample of CA adopters (524 farmers), with M&L being the mean comparison between moderate and low, H&L being the comparison between high and low, and H&M being a comparison between high and moderate adopters. The analysis of mean differences between adopters and non-adopters included the outcomes and the covariates.
Source: The United Republic of Tanzania (2020)

3.3 Model specification

The National Sample Census of Agriculture (NSCA) survey of Tanzania (The United Republic of Tanzania (2020) indicates that the farming systems used for analysis include that farmers adopted spatial and temporal CA technologies such as contours, planting legumes, organic fertilisers, covering soil and fallowing. For simplicity of analysis and information retention, we classified the technologies into groups of low-, moderate- and high-CA intensity adopters.

The adoption and assignment of these groups are not random among smallholders. Farmers' decisions to adopt are affected by several factors, such as socioeconomic status, cultural elements, goals, attitudes, knowledge and skills, biophysical and institutional considerations (Ma *et al*. 2018). The non-randomness of the farmers' choice to adopt a crop-farming system may give rise to the threat of sample selection bias. For instance, if the farmers experience poor farm or financial performance, they are more likely to adopt the highest levels of CA if, and only if, they can reduce farm management risks. In this situation, there is a farmer's potential selection bias and inaccurate treatment effect estimation. Addressing the selection bias is important for consistency and unbiased estimates.

Studies on the impact evaluation of programmes in agriculture adopt models such as propensity score matching (PSM) and endogenous switching regression (ESR), which involve two stages of estimations (Pufahl & Weiss 2009; Abdulai 2016; Zougmoré *et al*. 2016; Amadu *et al*. 2020; Akter *et al*. 2022). These studies assume that the treatment variable is dichotomous in nature and modelled using either logit or probit as selection equation in stage one of estimation, whereas the outcome equation is estimated in stage two.

Existing studies on the estimation of the causal effects under binary treatment for the assumption of conditional independence have been applied in the impact evaluation literature (Imbens 2004; Heckman & Vytlacil 2007; Wooldridge 2007). However, in some situations it may result in a loss of information.

In our study, the intensity of CA adoption (the treatment variable) was collapsed to take multiple values (here of low, moderate and high) to avoid the information loss in the model analysis (Cattaneo 2010; Cattaneo *et al*. 2013; Ma *et al*. 2018).

Further, with a multivalued treatment variable, the Bourguignon, Fournier and Gourgand (BFG) approach is proposed to address the selection bias (Bourguignon *et al*. 2007). However, the BFG method fails to estimate the average treatment effects of one group of CA intensity adoption relative to another. The approach can only estimate the determinants of the farmer's decision to choose a level of CA adoption and the specified outcomes.

As a response to the weakness of the BFG method, we adopted a multivalued treatment effects model to be able to estimate the average treatment effects of different choices of CA adoption (Ma *et al*. 2018). The multivalued treatment effect method has recently gained attention in impact evaluation studies. The method can estimate the coefficients of the average treatment effects while addressing the sample selection bias following the non-randomness of assigning farmers to the levels of CA adoption (Cattaneo 2010; Cattaneo *et al*. 2013; Binam *et al*. 2015; Uysal 2015; Esposti 2016; Ma *et al*. 2018; Smale *et al*. 2018; Kanyenji *et al*. 2022; Asante *et al*. 2024; Obi *et al*. 2024)

For the farmer to maximise the outcome variables (crop and financial performance) under the multivalued treatment effects model, he or she is obliged to choose a particular level of CA adoption from among the available alternatives (Ma *et al*. 2018; Asante *et al*. 2024; Obi *et al*. 2024), as in Equation (3).

$$D_{it}(T_i) = \begin{cases} 1, \text{if } T_i = t \\ 0, \text{otherwise} \end{cases} \tag{3}$$

For each farmer there is a set of potential outcomes such that $Y_{i0} - Y_{ik}$. Y_{it} represents the outcome for each farmer (i) for which $T_i = t$, where $t \in \mathfrak{T} = (0 \ldots \ldots K)$. For each farmer, ($i$), it is possible to observe only one potential outcome under the treatment status. The observed outcome, Y_{it}, can be represented in the form of treatment $D_{it}(T_i)$ and the potential outcomes Y_{it} (Rubin 1974; Uysal 2015; Ma *et al*. 2018), such that

$$Y_i = \sum_{t=1}^{K} D_{it}(T_i) Y_{it} \tag{4}$$

According to Lechner (2005), a farmer's pairwise treatment effects can be defined in a multivalued treatment framework, such as the average effect of treatment m relative to treatment l.

Let μ_k represents the unconditional mean, $E[Y_{ik}]$, and $\mu_{k|l}$ represents the conditional mean, $E[Y_{ik}|T_i]$, for k, $l = \{0, \ldots \ldots, K\}$. Accordingly, we can measure the mean effect of treatment over the entire population, as in Equation (5):

$$\tau_{ml} = E\,[\,Y_{im} - Y_{il}] = \mu_m - \mu_l \tag{5}$$

We further modelled the expected effect for a farmer randomly drawn from the population of participants with treatment m (Imbens 2004; Uysal 2015), such that

$$\gamma_{ml|m} = E\,[Y_{im} - Y_{il}|T_i = m] = \mu_{m|m} - \mu_{l|m}\,. \tag{6}$$

Note that only one of the potential outcomes can be observed. The defined averaged treatment effects cannot be revealed in the observed data, otherwise some assumptions will be imposed. The multivalued treatment effects model makes two assumptions to be able to establish the parameters of a randomised estimation (Uysal 2015; Ma *et al*. 2018). They are the conditional independence assumption (CIA) (Imbens 2000) and the strict overlap assumption (SOA) (Cattaneo 2010; Linden *et al*. 2016).

The unconfoundedness or selection-on-observables assumption (CIA) is the central principle of observability that generates dependence. Here, CIA implies that, once the pretreatment status represented by X_i is addressed, the choice of various levels of CA adoption intensity is random and not correlated with potential outcomes (crop yields and financial profits) (Ma *et al*. 2018). We express the assumption as elaborated on by Imbens (2000), such that

$$Y_{it} = \perp D_{it}|X_{it},\ \forall t\ \in \Psi, \tag{7}$$

where $\perp$ represents the independence nexus treatment variable D_{it} and outcome variable Y_{it}, conditional on the predictors (covariates) X_{it}.

This assumption is strong and requires that there are no observed predictors/factors such as climate change conditions and personal preference that influence a farmer's decision regarding a particular level of CA adoption intensity in a crop farming system and the outcomes (yields and profits). The coefficients estimated will be biased if this assumption is violated (Ma *et al*. 2018).

Furthermore, the CIA assumes that there are a sufficient set of explanatory variables for the treatment variable that are included in a set of covariates, such that adjusting for differences in this vector of covariates leads to valid estimates of the average treatment effects (Imbens & Wooldridge 2009; Uysal 2015; Ma *et al*. 2018). Subsequent studies have supported the premise that having a rich set of preprogramme data improves the assumption of conditional independence by allowing one to control for as many as possible observed statuses that are likely to influence the selection of a particular level of CA adoption (Khandker *et al*. 2010; Binam *et al*. 2015; Ma *et al*. 2018).

The overlap assumption states that, of all potential predictors, X_i, in the population, there is a potential strict positive probability that a farmer with such a covariate can be assigned to each treatment level. This implies that when the strict overlap assumption is not met, we cannot account for unobserved outcomes for farmers (Ma *et al*. 2018), and the results are potentially imprecise. The potential outcomes are stated as in Equation (8) below:

$$0 < \Pr[T_i = t | X_i = x], \forall t \in \Psi \tag{8}$$

The intuitive element from both assumptions is that the treatment framework and potential outcomes for each small-scale farmer are uncorrelated with the potential treatment status and outcomes of all farmers in the population (Binam *et al*. 2015; Uysal 2015; Ma *et al*. 2018).

If these two assumptions hold, one can use a propensity score regression adjustment to estimate K conditional mean functions by a parametric regression to estimate the treatment effects (Uysal 2015). The conditional expectation of the potential outcome for treatment t is identified by the conditional observed outcome for an individual receiving treatment t, and can be stated as follows:

$$E[\mathrm{Y}_{it}|X_i] = E[\mathrm{Y}_i|T_i = t, X_i] = \mathcal{B}_{0t} + X_t'\mathcal{B}_{1t}, \forall t \in \Psi, \tag{9}$$

where $\mathcal{B}_t = [\mathcal{B}_{0t}\, \mathcal{B}_{1t}']'$ represents the vector of unknown parameters, whereas $\mathcal{B}_{1t}$ contains the same dimension as X_i.

In relation to the higher dimension of X_i, impact evaluation studies introduce the generalised propensity score (GPS) to serve as a practical alternative to conditioning directly on X_i in the situation of multivalued treatments, as pioneered by Imbens (2000). Intuitively, the GPS refers to the conditional probability that a smallholder farmer i chooses a particular level of CA adoption from among the alternatives in a pre-treatment characteristic, X_i (Cattaneo 2010; Binam *et al*. 2015; Uysal 2015; Ma *et al*. 2018). We express the condition in the following equation:

$$r = (t, x) \equiv \Pr[T_i = t | X_i = x] = E[D_{it}(T_i)|X_i = x], \tag{10}$$

where the ordered logit or probit can be used to estimate the $r = (t, x)$ under a certain status of levels or values of the treatment.

We employed the GPS to weigh the observations to get a sample to balance the covariates in all treatment categories. We then calculated the average outcome for those treatments to $T_i = t$ in a sample to estimate $E[\mathrm{Y}_{it}|X_i]$, as in Equation (9) (Feng *et al*. 2012; Ma *et al*. 2018)

After obtaining the parameter vector $\mathcal{B}_t$ as it appears in Equation (9), the average treatment effect of treatment m relative to treatment l to get the ATE_{ml} can be consistently obtained from the next equation.

$$ATE_{ml} = (\beta_{0m} - \beta_{0l}) + \frac{1}{N}\sum_{i=1}^{N} X_i' (\beta_{1m} - \beta_{1l}), \tag{11}$$

where N is the total number of populations that received the treatment $T_i = m$ and $T_i = l$; $m, l \in \Psi = (1, 2. \dots \dots . \mathrm{K})$. In our survey data, $\mathrm{K} = 1$ is the low level of CA adoption, $\mathrm{K} = 2$ represents moderate CA adoption, and $\mathrm{K} = 3$ denotes high CA adoption.

For precise and strong comparisons among estimates, we employed regression adjustment (RA), inverse probability weighting (IPW), AIPW and IPWRA estimators from previous studies using a multivalued treatment framework to estimate the average effect of treatment level m relative to l (Cattaneo *et al*. 2013; Binam *et al*. 2015; Linden *et al*. 2016; Ma *et al*. 2018; Smale *et al*. 2018; Asante *et al*. 2024). If the model lacks functional form assumptions about the probability of the treatment or outcome variables, the RA and IPW estimators are applied.

Furthermore, AIPW and IPWRA estimators for both the treatment and outcome variables are considered doubly robust estimators. We consistently estimated the treatment effects, even if either the treatment or outcome variable model was incorrectly specified but another model was correctly specified. The AIPW contains IPW, which makes corrections for a mis-specified treatment model, while the IPWRA estimator contains the RA estimator, which employs IPW to make corrections when there is functional regression that is incorrectly specified (Cattaneo *et al*. 2013; Binam *et al*. 2015; Linden *et al*. 2016; Ma *et al*. 2018; Smale *et al*. 2018; Asante *et al*. 2024).

4. Data analysis

4.1 Empirical results and discussion

In this section we report on the quasi-experimental analysis we conducted of the impact of conservation agriculture on farm and financial performance by employing doubly robust (AIPW and IPWRA) estimators (Manda & Alene 2018; Asante *et al*. 2024). We performed the analysis using a command, 'teffects', along with other commands and specifications such as standard errors in AIPW and IPWRA, to address potential heteroscedasticity in our observational data (Uysal 2015; Ma *et al*. 2018; Manda & Alene 2018; Asante *et al*. 2024) using Stata version 18.

The econometric analysis summarised in Table 3 presents the average treatment effects for the pooled sample. We applied the logit model to reveal the determinants of the intensification of CA adoption while the dependent variable is a binary (adopters and non-adopters).

Table 3 shows that the adopters of CA outweigh the non-adopters in all the variables we measured. The second and fourth columns of Table 3 show the average treatment effect (ATE) coefficients from the AIPW and IPWRA estimators, respectively. The robust standard errors are in parentheses, and we specified them to control for potential heteroscedasticity. We applied the natural log to make the outcome variables more suitable for data in the regression model.

The impact of the treatment on gross maize yields is the log of 0.362 kg and is statistically significant at 1% in both doubly robust estimators. Regarding maize productivity per area planted, the adopters of maize still outweigh the non-adopters by the log of about 0.373 kg, which is statistically significant at 1%. Regarding the operational expenses (costs), adopters presented excessive costs compared to non-adopters. The adoption of CA technologies involves costs and has implications for farming. The adopters outweighed the non-adopters by a log of about 0.320 TZs, which is statistically significant at 10%.

The profits generated are higher for the adopters than the non-adopters. The adopters gained more in gross maize yields because they improved soil management and received more revenue after selling compared to the non-adopters, who maintained the status quo. The profit for adopters is the log of about 0.554 TZs higher than for the non-adopters, and is statistically significant at 10%. Finally, we evaluated the return on investment to know what this measure would be for both adopters and non-adopters. The costs of investment affect profits and RoI. However, the adopters still outweighed the non-adopters by a log of about 0.212 TZs, at a level of statistical significance of 5%. The results in Table 3 are in alignment with previous studies that evaluated the impact of conservation agriculture on farm performance in the SSA, with case studies in Tanzania and Malawi (Abdulai 2016; Mkonda & He 2017; Selejio *et al*. 2018). Furthermore, using global data, the systematic meta-analysis approach confirms that conservation agricultural technologies improve soil management, and hence crop production, in a context-specific situation (Li *et al*. 2019).

Table 3: Average treatment effect (ATE) of treatment (AIPW and IPWRA estimators) for pooled sample (adopters and non-adopters) (N = 1 009)

Outcome variables	ATE estimates: AIPW		ATE estimates: IPWRA	
	Coef. (std. error)	z-value	Coef. (std. error)	z-value
Gross maize yields	0.362 (0.134)***	2.71	0.362 (0.134)***	2.71
Maize productivity	0.373 (0.141)***	2.65	0.372 (0.141)***	2.64
Variable costs	0.320 (0.182)*	1.76	0.318 (0.181)*	1.75
Profits	0.554 (0.300)*	1.85	0.550 (0.300)*	1.84
Return on investment (RoI)	0.212 (0.105)**	2.01	0.215 (0.105)**	2.04

Note: *, ** and *** represent significance of the 10%, 5% and 1% levels, respectively.
Source: The United Republic of Tanzania (2020)

Table 4 shows the results from the multivalued treatment framework of the intensity of CA adoption, with the three levels. We investigated the effects of adopting lower, moderate and higher levels of CA on a plot/farm and the resultant financial gains. This showed the effects of the coefficients of movement from a particular adoption level, *k*, in the maize cultivation system, *m*, on the specified outcomes. We presented different pairwise comparisons of the adopter sub-sample for the three levels of CA adoption.

The second column in Table 4 presents the results from the AIPW estimator, and the robust standard errors are in parentheses. The results indicate that the adoption of a higher level of CA exerts a positive and statistically significant effect on maize farming in areas affected by climate change across all outcomes. Specifically, the estimated ATE of shifting from low to moderate CA adoption on gross maize harvest is the log of 0.473 kg and is statistically significant at 10%. The effect of moving from low to high and from moderate to high CA adoption on gross maize harvest is 0.578 kg and 0.849 kg, respectively, and is statistically significant.

The rest of the results indicate the same trend – that shifting from a lower level of adoption improves performance in maize farming and profit gains. With regard to maize production per cultivated area in hectares, moving from low to moderate adoption of CA gives rise to an increase of about the log of 0.511 kg of maize and is statistically significant at 10%. Movement from low to high and from moderate to high levels of CA adoption increases maize productivity per hectare by the log of 1.081 kg and the log of 3.473kg, and is statistically significant at 10% and 1%, respectively.

The interesting thing about farm operation expenses is that, as the farmers increase the levels of CA technologies on their plots, the costs increase too. For instance, the cost from low to moderate increases by about the log of 0.729 TZs and is statistically significant at 1%. Furthermore, the shift from low to high or from medium to high raises the costs of operating a maize farm by about the log of 2.405 TZs and about the log of 3.531 TZs, respectively. The increase in these operational costs is statistically significant at 1% and 10%, respectively.

One important aspect is that moving from low to high shows greater differences in most of the selected outcomes. Furthermore, the RoI that involves the consideration of expenses from farm operations is too high for adopters in a higher category. In comparison, higher adopters get less than the moderate adopters in terms of RoI for about the log of -1.502 TZs, and this is statistically significant at 1%.

The findings reveal that adopting a higher CA level augments yields, productivity, costs and profit, but does not do so consistently, and significantly improves performance in RoI due to the proportional uplifting of the operating costs. The results caution all stakeholders in the agricultural sector to be conscious of the combination of CA technologies and relatively low costs.

Farmers received the same market prices. Up-scaling the use of CA technologies when hoping to increase maize harvest eventually increases revenue, productivity, profitability and return on investment; being conscious of the operating costs is important. These influences farm performance and have financial implications for the revenue due to a substantial increase in operating expenses.

Farmers require intricate knowledge regarding their selection of CA technologies to adopt with reference to finance and management skills. This knowledge can be improved through extension service officers and farmers' cooperatives and organisations.

In the fourth column of Table 4 we show the results from IPWRA for comparison and confirmation of the robustness of the results from both the AIPW and IPWRA estimators. Like the AIPW results, the IPWRA possesses the same doubly robust property configuration as the existing impact evaluation studies (Linden *et al*. 2016; Ma *et al*. 2018). The results reveal that the average treatment effects (ATE) for treatment m relative to treatment k are likely to be those already explained in column 2 of Table 4.

Both estimators confirm the robustness of the results of the ATEs, such that the findings of this study are in line with the findings in the existing literature. The ATEs for the multivalued treatment using a doubly robust estimator give unbiased coefficients in the regression (Asante *et al*. 2024; Obi *et al*. 2024). The existing literature on the multivalued treatment effects model analyses the impact of conservation contextually. It mostly evaluates the impact on yields per hectare and some selected outcomes in this paper, such as the gross maize harvest, align with the existing findings that the level of CA adoption affects crop yields accordingly (Smale *et al*. 2018; Li *et al*. 2019; Asante *et al*. 2024).

We further provided more insight into the impact of the three levels of intensity of CA adoption on the selected outcomes. We analysed the average treatment effects on the treated (ATT) from propensity score matching. We compared and robust checked the results from the two doubly robust estimators. Our aim was to provide a comprehensive understanding of the impact of the intensification of CA adoption on agricultural and financial performance.

We present the results in graphical form in Figure 2 for simplicity. The results indicate that the adoption of a higher level of CA improves farm performance more than lower levels of CA adoption. The movement from low to moderate to high levels of CA adoption augments gross maize yields, maize productivity, operational expenses, profit margins and return on investment. Figure 2 shows the same patterns for moving from low to high levels of CA adoption, while there is a bigger gap than in the sequential movement from low to moderate to high levels. When adopters move from low to high levels of CA adoption, they improve farm and financial performance. The related explanation has already been given in Tables 3 and 4.

Table 4: Average treatment effect (ATE) of treatment m relative to treatment k (AIPW and IPWRA estimators) for the adopter sub-sample (N = 524)

From k to m	ATE estimates: AIPW		ATE estimates: IPWRA	
	Coef. (Std. error)	z-value	Coef. (Std. error)	z-value
Maize yields				
From low to medium	0.473 (0.247)*	1.92	0.427 (0.242)*	1.76
From low to high	0.578 (0.189)***	3.05	0.525 (0.152)***	3.46
From medium to high	0.849 (0.468)*	1.82	0.732 (0.389)*	1.88
Maize productivity				
From low to medium	0. 511 (0.265)*	1.80	0.398 (0.241)*	1.65
From low to high	1.081 (0.595)*	1.82	0.726 (0.401)*	1.81
From medium to high	3.473 (1.280)***	2.71	3.326 (1.178)***	2.82
Variable costs				
From low to medium	0.729 (0.237)***	3.08	0.702 (0.224)***	3.13
From low to high	2.405 (0.748)***	3.22	2.547 (0.7)***	3.64
From medium to high	3.531 (1.608)**	2.20	4.636 (2.277)**	2.04
Profits				
From low to medium	0.934 (0.507)*	1.84	0.857 (0.494)*	1.74
From low to high	4.223 (2.31)*	1.83	3.071 (1.106)***	2.78
From medium to high	2.304 (1.377)*	1.67	2.387 (1.375)*	1.74
RoI				
From low to medium	0.375 (0.227)*	1.65	0.385 (0.222)*	1.73
From low to high	0.586 (0.341)*	1.72	0.461 (0.254)*	1.82
From medium to high	-1.502 (0.418)***	-3.59	-1.371 (0.371)***	-3.70

Notes: *, ** and *** represent significance of the 10%, 5% and 1% levels, respectively; robust standard errors are in parentheses.
Source: United Republic of Tanzania (2020)

The interesting thing, however, is in relation to return on investment. When adopters shifted from moderate to higher levels of CA adoption, they got about 37.03% RoI. This reflects the doubly robustness of the estimators in Table 4.

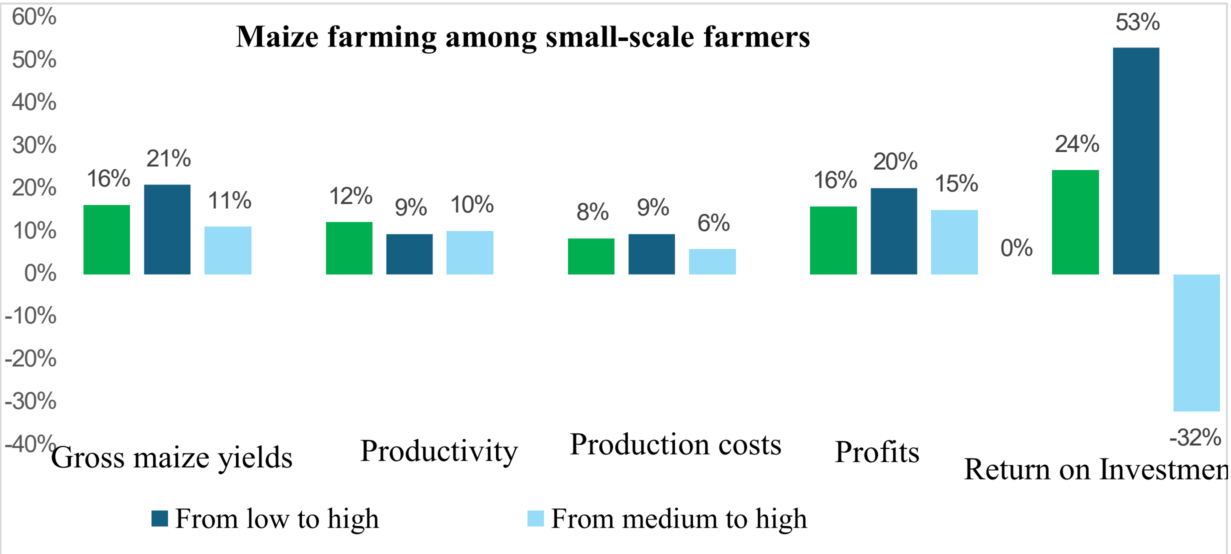

Figure 2: Percentage change in average treatment on the treated (ATT)
Source: The United Republic of Tanzania (2020)

4.2 Study limitations

There might be limitations emanating from self-reported cross-sectional data which might contain recalling bias leading to inaccuracy information during the survey. Panel data thought to provide more comprehensive insights about CA intensity adoption and the long effects on farm and profitability performance.

Another limitation is the scope of the study, which focused only on the Tanzanian context, although it is potentially informative for similar settings as it covers climate conditions, geographical context and farmers' practices. A cross-country study would provide comprehensive conclusions. Future studies can focus on panel data and include a cross-country scope of the role of CA in managing crop production and financial risks in the long run, given the effects of climate change and land degradation.

5. Conclusion and policy implications

We investigated the impact of intensification of CA adoption on maize and financial performance. We applied a multivalued treatment framework to the selected outcomes after controlling for confounding factors. The results reveal that scaling up from lower to higher levels of CA adoption improves performance in terms of yields, productivity, profits and RoI. However, higher levels of CA adoption mean higher costs, which subsequently reduce RoI.

The increase in operating expenses is associated with the scaling up of CA adoption. The impact of production costs is felt more when adopters move from moderate to higher levels of adoption. We found that shifting from moderate to high reduces the RoI in both doubly robust estimators due to the potential increase in operating costs.

The results suggest that, when shifting from one level to another, farmers should consider the operating expenses that influence yields and eventually the profit gains and RoI. The findings suggest that farmers should target maize harvest augmentation. Also, it is crucial that there are financial gains to realise profits and RoI in agriculture, which corresponds to farm operating costs.

Planning for the intensification of CA adoption in farming systems should align with the minimal costs of farm inputs and capital investment. To improve farm performance, production and capital efficiencies are paramount to increase profitability. The adoption of CA is effectively replacing the traditional practice of relying only on the harvest, without considering the corresponding financial risks.

The policy implication of the findings is that there is a role for every stakeholder to help small household farmers to scale up CA intensification. They should elucidate the role of institutions, extension services and market structures in enabling profitable CA adoption. The policy can target subsidies for inputs, training in cost-effective combinations of CA practices, or financial support mechanisms. Farmers should be encouraged to set production objectives and targets for financial gains, while being conscious of the corresponding farm operating costs.

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