Economic Determinants of IR2793-80-1 Rice Yield in Bunyala Irrigation Scheme, Kenya: Evidence from Comparative Production Function Modelling

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ABSTRACT

Rice productivity in Kenya remains below domestic demand despite continued investment in irrigation and improved varieties. This study analysed the economic determinants of IR2793-80-1 paddy yield among smallholder farmers in Bunyala Irrigation Scheme, Kenya, and examined whether the commonly used Cobb-Douglas production function adequately represented the observed input-output relationships. An explanatory cross-sectional survey design was adopted. A target sample of 333 farmers was determined, 266 questionnaires were administered, and 258 complete responses were retained for analysis. Paddy yield was measured in kilograms per acre; inorganic fertiliser was converted into formulation-adjusted nutrient quantity per acre; farm size was measured as acreage planted with IR2793-80-1; labour as person-days per acre; and productive credit as borrowed funds used directly for rice production per acre. Descriptive statistics and Spearman correlation preceded Ordinary Least Squares estimation of Linear, Cobb-Douglas and centred Translog production functions. The Cobb-Douglas benchmark explained 35.8% of variation in logged yield, whereas the centred Translog model explained 50.9%. The flexible terms significantly improved explanatory power ($\Delta R^2 = .151$; F-change = 7.484, $p < .001$), while AIC and BIC also favoured the Translog specification. In the preferred model, land (B = .217, $p < .001$), labour (B = .151, $p < .001$) and productive credit (B = .030, $p < .001$) had positive first-order effects at the mean input combination. Fertiliser and credit exhibited significant positive curvature, land showed diminishing curvature, and the labour-credit interaction was negative and significant. The findings demonstrate that IR2793-80-1 yield is characterised by nonlinear and interdependent input relationships. The study recommends coordinated nutrient management, manageable acreage, timely labour organisation and production-linked credit rather than isolated increases in individual inputs.

Keywords: IR2793-80-1 rice; rice productivity; Bunyala Irrigation Scheme; productive credit; Translog production function

INTRODUCTION

Rice is a strategic food crop whose productivity has direct implications for food security, household income, rural employment and agricultural transformation. Globally, rising population, urbanisation and changing consumption patterns continue to increase demand for rice, placing pressure on producing countries to raise output per unit of land rather than rely only on acreage expansion (Bandumula, 2018; Samal et al., 2022). In Sub-Saharan Africa, the relationship between agricultural production, food availability and wider market conditions further reinforces the importance of productivity-enhancing strategies (Kuso & Gachunga Muhia, 2019a). For Kenya, national rice policy has similarly emphasised increased domestic production through irrigation development, improved technologies and stronger farmer support in order to narrow the persistent production-consumption gap (Ministry of Agriculture, Livestock, Fisheries and Irrigation, 2019; Africa Rice Centre, 2021).

Bunyala Irrigation Scheme in Busia County is one of Kenya's established rice-producing areas and forms part of the national effort to expand irrigated agriculture (National Irrigation Authority, 2022). Evidence from Kenyan irrigation systems indicate that improved water management, production technologies and farmer-level management play critical role in improving rice productivity, but outcomes remain sensitive to the way complementary inputs are organised (Mati et al., 2021; Ouma et al., 2024). Farmers in Bunyala work in a general common irrigation system but are not the same in respect of plot size, labour organisation, management, access to finance, and quantities and timing of inputs used. These differences can generate substantial variation in paddy yield even where farmers cultivate the same variety. The present study focused specifically on IR2793-80-1, locally known as Sindano, during the 2025 production season.

Four measurement and evidence problems motivated the analysis. First, variety-specific evidence for IR2793-80-1 in Bunyala remains limited relative to better-studied irrigation schemes such as Ahero and Mwea, where previous studies have examined rice productivity, technical efficiency and management practices (Abong'o, 2016; Omondi & Shikuku, 2013; Ndiiri et al., 2017). Second, fertiliser is often recorded as kilograms of physical product even though equal weights of urea, diammonium phosphate, sulphate of ammonia and different NPK grades do not contain equal quantities of plant nutrients; contemporary evidence also shows that rice response depends on nutrient balance and management rather than undifferentiated product weight (Johnson et al., 2023; Qiu et al., 2022). Third, credit is frequently represented as a yes/no access variable, which does not show how much borrowed capital was actually committed to production, despite evidence that the productivity effect of finance depends on adequacy, timing and productive use (Adjognon et al., 2017; Houngue & Nonvide, 2020; Ssengonzi et al., 2025). Labour is also commonly recorded without standardising the actual person-days used per acre, yet labour timing and organisation can influence agricultural productivity substantially (Nakano et al., 2016; Sadiq et al., 2022).

A fourth problem concerns functional form. Cobb-Douglas is widely used in agricultural economics because it is parsimonious and its log-linear coefficients are readily interpreted as constant elasticities (Cobb & Douglas, 1928; Gujarati & Porter, 2009). However, it excludes squared and interaction effects and can therefore impose restrictions that are too strong where marginal productivity changes with input intensity or where inputs interact. The Translog production function relaxes these restrictions by allowing curvature and interdependence among inputs (Christensen et al., 1973; Wijetunga, 2016). This distinction is important in rice production because fertiliser response may change with application level, larger acreage may strain complementary resources, and credit may influence productivity differently depending on labour and other input combinations. Comparative functional-form testing therefore provides a stronger basis for empirical inference than assuming a single specification in advance (Greene, 2018; Wooldridge, 2016).

Against this background, the study analysed the effects of formulation-adjusted fertiliser nutrients, farm size, labour input and productive credit on IR2793-80-1 paddy yield in Bunyala Irrigation Scheme. The study responds to calls for more context-specific analysis of agricultural productivity in Kenya, where institutional interventions and input support can affect farm performance but their effectiveness depends on the conditions under which farmers use productive resources (Ochieng & Kuso, 2026; Ouma et al., 2024). It also compared a Linear benchmark, a Cobb-Douglas theory-based benchmark and a centred Translog model to establish whether the constant-elasticity restrictions of Cobb-Douglas were supported by the data. The contribution is therefore both substantive and methodological: it provides scheme- and variety-specific evidence, improves the measurement of fertiliser and productive credit, and demonstrates how functional-form choice can materially change conclusions about agricultural inputs.

LITERATURE REVIEW AND THEORETICAL FRAMEWORK

Production theory and functional form

The study was anchored in neoclassical production theory, which explains how producers transform inputs into output subject to technology and resource constraints. In the present setting, fertiliser represented a material nutrient input, farm size represented land committed to the focal variety, labour represented human effort, and productive credit represented financial capital used to obtain production inputs. The general relationship can be expressed as $Y = f(F, S, L, C, \varepsilon)$, where Y is IR2793-80-1 paddy yield per acre; F is formulation-adjusted fertiliser nutrients per acre; S is acreage planted with IR2793-80-1; L is labour person-days per acre; C is productive credit per acre; and ε captures omitted and random influences such as soil fertility, water reliability, pest pressure, weather, extension support and farmer management ability.

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Cobb and Douglas (1928) provided a parsimonious production function that remains widely used because its log-linear form yields directly interpretable input elasticities. In this study it was retained as the theory-based benchmark rather than assumed to be the final model. Its central limitation is the imposition of constant elasticities and the exclusion of curvature and interactions. The Translog function, introduced as a flexible second-order approximation, relaxes those restrictions and nests Cobb-Douglas as a special case when all squared and interaction terms are jointly zero (Christensen et al., 1973). Flexible Translog approaches have also been applied to rice production contexts (Wijetunga, 2016).

Accordingly, model choice was treated as an empirical question rather than a theoretical contest. The Linear model represented constant absolute effects in original units, Cobb-Douglas represented constant proportional effects, and Translog allowed input effects to vary with levels and combinations. The preferred specification was selected using adjusted R^2, standard error, a hierarchical F-change test, Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and diagnostic adequacy.

Empirical evidence on the four inputs

Fertiliser is a central determinant of rice productivity, but its effect depends on nutrient quantity, balance, timing, soil fertility and water management. Evidence from sub-Saharan Africa links inorganic fertiliser use to rice yield gaps, while wider agronomic evidence shows that the productivity of nutrient application is conditional on management and spatial context (Johnson et al., 2023; Snapp et al., 2023). This supports measuring fertiliser more carefully than by undifferentiated product weight. In the present study, labelled nutrient composition was used to standardise inorganic fertiliser products into comparable nutrient quantities per acre.

Farm-size effects are theoretically ambiguous. Larger farms may benefit from market orientation, coordinated purchasing and mechanisation, while smaller plots are associated with intensive labour and close supervision. The inverse size-productivity literature suggests management intensity and plot-level supervision as potential benefits of smaller plots, while scale-based arguments focus on access to complementary resources (Bevis & Barrett, 2020; Mahajan et al., 2017). This ambiguity suggests that the relationship between planted acreage and yield per acre may be nonlinear.

Rice cultivation remains labour-sensitive because land preparation, transplanting, weeding, bird control, water management and harvesting must occur within critical time windows. Evidence from African rice systems show that timely labour input and better labour organisation, and training on good management practices correlate with productivity (Nakano et al., 2016; Mabe, 2023). Labour quantity alone is therefore not sufficient, it requires timing and coordination with other inputs for yield improvement to occur.

Productive credit can relax liquidity constraints and enable farmers to purchase fertiliser, hire labour and complete land preparation on time. However, access alone does not guarantee higher productivity. Credit may be too little, too late, too expensive or diverted for non-production uses. Empirical evidence reveals that agricultural finance can boost productivity if it is effectively disbursed timely and to productive agricultural factors (Awotide et al., 2015; Houngue & Nonvide, 2020; Nguyen et al., 2023). However, weak or poorly-targeted credit has modest impact (Feder et al., 1990; Adjognon et al., 2017). These findings motivated measurement of the amount of borrowed funds actually used for IR2793-80-1 production per acre.

METHODOLOGY

Research design, sampling and data collection

The study adopted an explanatory cross-sectional survey design and a quantitative econometric approach. It was conducted in Bunyala Irrigation Scheme, Busia County, Kenya, among smallholder farmers cultivating IR2793-80-1 during the 2025 production season. The scheme was represented through stratified random sampling across 16 blocks or sections and 57 feeders or phases. A target sample of 333 farmers was determined. Of 266 questionnaires administered face-to-face, 258 were complete and retained for analysis,

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giving a completion rate of 97.0% among administered questionnaires and a usable response rate of 77.5% relative to the target sample.

Variable measurement

Primary data were collected using structured questionnaires. Paddy yield was calculated as total IR2793-80-1 paddy harvested divided by acreage planted with the variety and expressed in kilograms per acre. Fertiliser products were converted into formulation-adjusted nutrient quantities using labelled nitrogen, phosphorus and potassium composition and then standardised per acre. Farm size was measured as acres planted with IR2793-80-1 rather than total landholding. Labour was converted to person-days per acre. Productive credit was measured as the amount of borrowed funds used directly for rice-production activities per acre; farmers who used no productive credit were coded as zero. The econometric credit variable therefore captures the amount of credit actually committed to production rather than a binary measure of access. Credit source, borrowing cost, disbursement timing and cash-versus-in-kind terms were not entered as separate regressors, so the estimated credit relationship should be interpreted as an amount-used effect rather than a complete measure of credit quality.

Functional forms and estimation strategy

Descriptive statistics were used to summarise distributions. Because the original continuous variables departed significantly from normality, Spearman's rank-order correlation was used for preliminary bivariate analysis. Normality of predictors was not treated as an Ordinary Least Squares requirement; final diagnostic attention focused on residual behaviour, collinearity, influential observations and functional shape.

The three estimated functional forms were specified as follows:

Linear benchmark:

$$Y_i = \beta_0 + \beta_1 F_i + \beta_2 S_i + \beta_3 L_i + \beta_4 C_i + \varepsilon_i$$

Cobb-Douglas benchmark:

$$\ln(Y_i) = \beta_0 + \beta_1 \ln(F_i) + \beta_2 \ln(S_i) + \beta_3 \ln(L_i) + \beta_4 \ln(C_i + 1) + \varepsilon_i$$

Centred Translog model:

$$\ln(Y_i) = \beta_0 + \Sigma_j \beta_j x_{ji} + \tfrac{1}{2}\Sigma_j \gamma_{jj} x_{ji}^2 + \Sigma_{j<k} \gamma_{jk} x_{ji} x_{ki} + \varepsilon_i$$

where Y_i is IR2793-80-1 paddy yield per acre; F_i, S_i, L_i and C_i denote formulation-adjusted fertiliser nutrients, acreage planted with IR2793-80-1, labour person-days per acre and productive credit per acre, respectively. In the Translog model, x_j denotes the mean-centred logged input; the credit term is based on $\ln(C + 1)$. The Translog specification therefore retains the four first-order effects while adding four half-squared terms and six pairwise interaction terms, allowing both curvature and input interdependence.

The inferential strategy followed four stages. First, the Linear model was estimated as a basic level-level benchmark. Second, the Cobb-Douglas benchmark was estimated in logarithmic form, with productive credit transformed as ln(Credit + 1) to retain genuine zero-credit observations. Third, the logged inputs were mean-centred and extended through the squared and pairwise interaction terms shown above to estimate the centred Translog model. Fourth, Cobb-Douglas and Translog were formally compared using adjusted R^2, standard error, the hierarchical F-change test, AIC, BIC and diagnostic adequacy. AIC and BIC were compared only between the two log-yield models because the Linear model used the dependent variable in levels.

The four null hypotheses were assessed at the 5% significance level. Under Cobb-Douglas, each input was represented by one first-order elasticity. Under the preferred Translog model, an input's effect was represented by its first-order term together with its squared term and relevant interactions. Final conclusions therefore

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considered the statistically significant components associated with each input rather than relying on the first-order coefficient alone.

Ethical considerations

Participation was voluntary and based on informed consent. Personal identifiers were excluded from analysis and reporting, and findings were presented in aggregate form. Data were used for academic purposes, and the study sought to minimise harm while ensuring representation of different parts of the irrigation scheme.

RESULTS

Descriptive statistics and preliminary associations

Respondent demographic profile

The 258 valid respondents represented a varied smallholder-farmer population. Almost half (49.6%) were aged 31–45 years, while 30.6% were aged 46–60 years; 64.3% were male and 35.7% female. In terms of education, 38.4% had secondary education, 30.6% primary education, 24.0% tertiary education and 7.0% had no formal education. This profile indicates that the study captured farmers across different age and educational groups, including participants with limited formal schooling.

Table 1. Demographic profile of respondents (N = 258)

Characteristic	Category	Percent (%)
Age	18–30 years	9.7
	31–45 years	49.6
	46–60 years	30.6
	61+ years	10.1
Gender	Male	64.3
	Female	35.7
Education	No formal education	7.0
	Primary	30.6
	Secondary	38.4
	Tertiary	24.0

Note. N = 258. Percentages are based on valid responses from the field survey.

Table 2. Descriptive statistics of the main study variables (N = 258)

Variable	Mean	SD	Minimum	Maximum
Yield per acre (kg)	2,218.58	504.55	500.00	3,200.00
Fertiliser nutrients per acre (kg)	66.88	21.21	32.00	231.00
Labour input per acre (person-days)	68.63	28.46	16.00	160.00
Productive credit per acre (KES)	18,915	22,772	0	100,000
Land planted with IR2793-80-1 (acres)	2.05	1.73	0.20	8.00

Note. Farmers reporting no productive credit were coded as zero.

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Average yield was 2,218.58 kg per acre, with a standard deviation of 504.55 kg and a wide range from 500 to 3,200 kg. This variation confirmed substantial productivity differences among farmers cultivating the same rice variety within the same irrigation scheme. Formulation-adjusted fertiliser nutrients averaged 66.88 kg per acre, labour averaged 68.63 person-days per acre, productive credit averaged KES 18,915 per acre, and the mean area planted with IR2793-80-1 was 2.05 acres.

Spearman correlation provided preliminary bivariate evidence. Yield was positively associated with fertiliser ($\rho = .144$, $p < .05$), land ($\rho = .275$, $p < .01$) and labour ($\rho = .233$, $p < .01$), while the association between yield and productive credit was positive but statistically insignificant ($\rho = .095$). These coefficients were not treated as final effects because they did not hold the other inputs constant and could not represent nonlinear or interaction relationships.

Functional-form comparison

Table 3. Comparison of Cobb-Douglas and centred Translog log-yield models

Model	R^2	Adjusted R^2	Std. error	ΔR^2	F-change	AIC	BIC
Cobb-Douglas	.358	.347	.22879	—	—	-756.13	-738.36
Centred Translog	.509	.481	.20413	.151	7.484	-805.39	-752.10

Note. Both models use ln(yield per acre) as the dependent variable. The Translog model adds ten centred squared and interaction terms. The F-change for the added terms was significant at $p < .001$.

The Cobb-Douglas benchmark was statistically significant, $F(4, 253) = 35.206$, $p < .001$, and explained 35.8% of the variation in logged yield. Fertiliser ($B = .124$, $p = .023$), land ($B = .211$, $p < .001$) and labour ($B = .139$, $p < .001$) were positive and significant, while productive credit was effectively zero and insignificant in the restricted model. The Linear benchmark was also statistically significant, $F(4, 253) = 29.061$, $p < .001$, with an adjusted R^2 of .304, but its fit statistics were not directly compared with the log-yield models because the dependent variable was on a different scale.

The centred Translog model substantially improved fit. R^2 increased from .358 to .509 and adjusted R^2 from .347 to .481, while the standard error declined from .22879 to .20413. The ten added squared and interaction terms produced a significant F-change of 7.484. The full model was statistically significant, $F(14, 243) = 17.982$, $p < .001$. AIC and BIC were also lower for the Translog model despite its larger parameter count. These results rejected the adequacy of the Cobb-Douglas restrictions for the Bunyala data and justified using the centred Translog model for final interpretation.

Preferred centred Translog estimates

Table 4. Coefficients of the preferred centred Translog model

Term	B	SE	T	p
Centred fertilizer	.074	.053	1.403	.162
Centred land	.217	.017	12.655	< .001
Centred labour	.151	.031	4.829	< .001
Centred credit	.030	.006	4.909	< .001
Fertiliser squared	.532	.207	2.569	.011
Land squared	-.125	.042	-2.999	.003
Labour squared	.059	.090	.654	.514

Term	B	SE	T	p
Credit squared	.021	.004	5.505	< .001
Fertiliser × land	-.084	.066	-1.279	.202
Fertiliser × labour	-.109	.110	-.989	.324
Fertiliser × credit	.000	.011	.033	.974
Land × labour	.060	.039	1.554	.122
Land × credit	-.006	.004	-1.458	.146
Labour × credit	-.021	.006	-3.397	.001

Note. Dependent variable = ln(yield per acre). Squared variables were calculated as 0.5 multiplied by the squared centred log input. The model constant was 7.452 (SE = .050, $p < .001$).

Because the Translog inputs were expressed as mean-centred logarithms, the four first-order coefficients in Table 3 are local output elasticities evaluated at the sample-mean input combination. The squared and interaction coefficients show how those elasticities change as input levels or combinations move away from the mean. The article therefore interprets first-order, curvature and interaction terms jointly rather than treating the first-order coefficient as a constant elasticity over the full observed range.

Fertiliser had a positive but statistically insignificant first-order coefficient at the mean input combination (B = .074, p = .162), while the fertiliser-squared term was positive and significant (B = .532, p = .011). The fertiliser effect was therefore nonlinear rather than adequately represented by one constant elasticity. The positive curvature indicates that the marginal association became more positive over part of the observed nutrient range; it should not be interpreted as evidence that unlimited fertiliser application would continuously raise yield.

Land had a positive and significant first-order coefficient (B = .217, $p < .001$) together with a negative and significant squared term (B = -.125, p = .003). This pattern indicates a positive relationship around the mean farm size but diminishing yield gains as acreage under IR2793-80-1 increased.

Labour had a positive and significant first-order coefficient (B = .151, $p < .001$), while its squared term was insignificant. However, the labour-credit interaction was negative and significant (B = -.021, p = .001). This shows that the marginal contribution of labour varied with the level of productive credit, and vice versa, rather than the two inputs operating independently.

Productive credit was positive and significant in the preferred model (B = .030, $p < .001$), and the credit-squared term was also positive and significant (B = .021, $p < .001$). This contrasted sharply with the insignificant credit coefficient under Cobb-Douglas. The flexible model therefore revealed a nonlinear credit relationship that the constant-elasticity benchmark concealed.

Diagnostic assessment

Mean-centering reduced non-essential multicollinearity among the first-order, squared and interaction terms. The maximum Variance Inflation Factor in the final Translog specification was 4.862 and the maximum condition index was 11.163, indicating that collinearity was not severe enough to prevent interpretation. Cook's distance reached a maximum of .150, and no single observation dominated the model. Residual diagnostics showed approximate central normality but tail departures and some heteroscedasticity. The reported inference is based on the original OLS specification and does not present a separate heteroscedasticity-consistent (HC1–HC3) re-estimation. Consequently, coefficient signs, magnitudes and conventional significance levels are reported transparently, but statistical precision should be interpreted with appropriate caution where heteroscedasticity is present. The estimates are therefore treated as conditional econometric relationships within the sampled production season rather than universal experimental causal effects.

DISCUSSION

Fertiliser nutrients

The fertiliser result demonstrates why both improved measurement and functional-form testing matter. In Cobb-Douglas, fertiliser was found to have a positive constant elasticity. With Translog, the first-order coefficient at the mean was not significant while the coefficient for the squared term was significant, indicating that the relationship varied across nutrient levels. This is also in line with the neoclassical production theory, which states that the marginal product can vary with the level of input use, and with empirical evidence that rice response to fertiliser depends on nutrient balance, application intensity, soil conditions, water management and management quality rather than on quantity alone (Johnson et al., 2023; Qiu et al., 2022; Snapp et al., 2023). The finding therefore extends studies reporting positive fertiliser-productivity relationships by showing that an average elasticity can conceal variation across the observed input range.

The formulation-adjusted measure also improves substantive interpretation. If one kg of urea is used as a replacement for one kg of NPK or DAP, then the solution is not an accurate measurement, as their nutrient levels differ. Studies of fertiliser-use gaps and rice-yield performance similarly emphasise that nutrient composition, farmer application decisions and local production conditions matter for realised productivity (Islam et al., 2024; Johnson et al., 2023). Transforming physical products into nutrient quantities therefore reduces an important comparability problem. Nevertheless, the use of the composite nutrient measure is not meant to suggest that nitrogen, phosphorus and potassium are agronomically interchangeable. Practical implication is not just advice to apply more fertiliser in total, but rather formulation-specific guidance, with soil information and irrigation scheduling used wherever possible (Qiu et al., 2022; Snapp et al., 2023).

Farm size

In both the Cobb-Douglas and the Translog model, land was the largest first order predictor, and the negative squared term in both models indicated a decreasing yield advantage for the larger acreages of land. This finding helps reconcile competing arguments in the farm-size literature. The inverse size-productivity literature finds that smaller-farm benefits can be explained in part by the differential in supervision and management, while scale-based arguments focus on mechanisation, market orientation and access to complementary inputs (Bevis & Barrett, 2020; Mahajan et al., 2017). Evidence from Kenya also indicates productivity in irrigation systems is linked to management practices and the effective coordination of water and other resources, rather than to area irrigated (Mati et al., 2021; Ouma et al., 2024). The Bunyala result therefore suggests that some expansion may improve production organisation, but further expansion can stretch labour, supervision, irrigation control and working capital.

For Bunyala, the result does not support unrestricted acreage expansion. Land contributes to yield only if there are complementary inputs available at the right time; this is in line with production theory and evidence from African rice systems indicating that productivity outcomes depend on management, technology and complementary resources (Kijima et al., 2011; Nakano et al., 2016). Therefore, farmers and scheme managers should consider fertiliser, labour, finances, and irrigation timings for the planned acreage before planting.This aligns with the wider policy argument that agricultural support should focus on the productivity of resource use rather than expansion of a single input in isolation (Ochieng & Kuso, 2026).

Labour input

Labour remained a distinct and statistically important determinant of IR2793-80-1 yield. In the preferred centred Translog model, the first-order labour coefficient was positive and significant ($B = .151$, $p < .001$), while the labour-squared term was not significant. This indicates that, around the mean input combination, additional labour was associated with higher yield, but there was no evidence of a separate nonlinear labour effect over the observed range. This is economically viable since rice production is time sensitive, meaning that if the maximum yield is to be achieved, all the operations involved in rice production, such as land preparation, transplanting, weeding, bird control, water management and harvesting, have to be carried out at the proper times. Previous evidence from African rice systems similarly links timely labour allocation, improved management and labour-use efficiency with stronger productivity outcomes (Nakano et al., 2016; Mabe, 2023; Sadiq et al., 2022). The Bunyala finding thus reinforces the conceptualisation of labour as a production factor which should be viewed not only in terms of the hours supplied but also in terms of its value, arising from the need to deploy it at the right time and task organisation.

For farmers and extension services, the practical implication is to plan labour around critical crop operations rather than simply increase total labour days. When a farmer provides a large amount of labour, but the labour is provided after the critical time needed for a crop or if labour is not coordinated, the farmer may still have a poor return on labour. This understanding is in line with the results of research conducted by Nakano et al. (2016) and Mabe (2023) which showed that rice performance can be improved through management training and efficient organization of farm activities. For Bunyala, labour calendars linked to land preparation, transplanting, weeding, bird control and harvesting would therefore provide a more useful management tool than undifferentiated labour expansion.

Productive credit

Productive credit also emerged as an independent determinant of yield once the restrictive Cobb-Douglas form was relaxed. Under Cobb-Douglas, the credit coefficient was effectively zero and statistically insignificant. In the preferred centred Translog model, however, the first-order credit term was positive and significant ($B = .030$, $p < .001$) and the credit-squared term was also positive and significant ($B = .021$, $p < .001$). The change in inference across functional forms is important because it shows that the relationship between credit and yield was not adequately represented by one constant elasticity. This confirms the liquidity constraint argument which says that fairly strong, timely, and well-timed finance can support production, whereas poorly targeted, weak, or delayed finance can have limited productivity effects (Awotide et al., 2015; Adjognon et al., 2017; Houngue & Nonvide, 2020; and Nguyen et al., 2023). Evidence from East African smallholder settings also shows that access to microcredit can influence broader economic welfare, reinforcing the importance of examining how finance is actually used rather than treating access alone as sufficient (Ssengonzi et al., 2025).

The policy implication is therefore not simply to expand borrowing. Productive credit should be sufficient and available prior to the critical production operations and linked to a realistic production per acre budget. Financial institutions and farmer organisations should be mindful of the timing and purpose of credit loans as the productivity of credit is linked to when the credit is received by the farmer and how they spend it on fertiliser, labour and land preparation. This interpretation is consistent with evidence that agricultural credit contributes more effectively to productivity when it is combined with complementary inputs and appropriate farm management (Taremwa et al., 2021; Nguyen et al., 2023; Houngue & Nonvide, 2020).

Labour-credit interaction

Although labour and productive credit were analysed as separate study variables, the Translog specification also identified a statistically significant interaction between them. The labour-credit interaction coefficient was negative ($B = -.021$, $p = .001$), indicating that the marginal association of labour with yield varied with the level of productive credit, and equivalently that the marginal association of credit varied with labour input. This interaction does not mean that labour and credit are the same determinant, nor does it justify combining the two objectives. Rather, it shows that their effects were partly interdependent in the observed production system. Production theory allows such interdependence because the contribution of one input may depend on the availability and organisation of another (Christensen et al., 1973; Greene, 2018). The finding also accords with agricultural finance evidence emphasising that credit is most productive when it is coordinated with the inputs and operations it is intended to finance (Taremwa et al., 2021; Nguyen et al., 2023).

The negative sign should nevertheless be interpreted cautiously. The cross-sectional design does not establish whether the interaction arose from poorly timed labour expenditure, substitution between hired labour and other financed inputs, differences in management ability, or another unobserved mechanism. Accordingly, the study does not recommend reducing either labour or credit. Its defensible implication is that finance and labour planning should be coordinated: credit should reach farmers before labour-intensive operations, and labour expenditure should be assessed alongside fertiliser, land preparation and other competing uses of borrowed funds. This cautious interpretation is consistent with the study's broader treatment of the estimated coefficients as conditional econometric relationships rather than experimental causal effects.

Implications of functional-form choice

The comparative modelling exercise is a central methodological contribution of the study. Had the analysis stopped at Cobb-Douglas, it would have concluded that fertiliser, land and labour were significant constant-elasticity determinants and that credit was insignificant. However, production theory does not dictate the adoption of a single functional form, and flexible specifications are of particular value if the value of the marginal effects can change with the level of input(s) used (Christensen et al., 1973; Greene, 2018). The centred Translog model, on the other hand, revealed non-linear impacts of fertiliser, land and credit use, as well as significant interaction between labour and credit. This result is consistent with the rationale for flexible modelling in rice production reported by Wijetunga (2016) and demonstrates that model choice can affect not only goodness of fit but also substantive policy conclusions.

This does not imply that Cobb-Douglas was an inappropriate starting point. It is parsimonious and provides theoretical clarity and elasticity interpretation making it a defensible benchmark in the agricultural production analysis (Cobb & Douglas, 1928; Gujarati & Porter, 2009). However, retaining it without testing its restrictions would have concealed important curvature and interaction in the Bunyala data. The sequence adopted in this study, which involves a benchmark estimation stage, a flexible extension stage and a formal comparison and a diagnostic assessment stage, then yields a more transparent framework for choosing a model (Greene, 2018; Wooldridge, 2016). The methodological lesson is that functional form should be tested empirically where economic theory and prior evidence provide plausible reasons to expect nonlinear or interdependent input effects.

The preference for Translog should nevertheless be understood as evidence from the observed sample rather than proof that the same specification will dominate in every sample or season. The significant hierarchical F-change shows that the ten added terms jointly improved explanatory power, while the lower AIC and BIC values provide complexity-penalised support for the flexible model. These criteria reduce, but do not eliminate, concern that a richer specification can capitalise on sampling variation. Cross-validation, bootstrap stability analysis and out-of-sample prediction were not part of the reported analysis; replication across seasons and independent samples is therefore needed to establish the stability of the significant curvature and interaction terms.

Identification, omitted variables and contextual applicability

The cross-sectional design creates an identification limitation because some determinants of yield were not directly measured in the production function. Soil fertility, water reliability, pest and disease pressure, weather conditions, extension contact, farmer experience and management ability may be correlated with both observed inputs and yield. The direction of any resulting omitted-variable bias is not necessarily uniform. For instance, when the effectiveness of fertiliser application and the efficiency of labour organisation are increased, then part of the estimated fertiliser or labour association could reflect management ability and be biased upward. Conversely, farmers provided with less reliable soil and/or water resources might increase fertiliser use and/or borrow more money to overcome adverse conditions, which could attenuate or even reverse observed input coefficients. Productive credit may also be correlated with commercial orientation, risk tolerance and management capacity. These possibilities reinforce the interpretation of the coefficients as conditional associations rather than isolated causal effects.

The findings are therefore most directly applicable to smallholder farmers cultivating IR2793-80-1 under irrigated conditions similar to those observed in Bunyala during the study season. The possibility of transfer to other schemes is more likely to be feasible where farmers are exposed to similar soil types, water supply,

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fertiliser availability, labour markets, credit availability and extension services. The results should not automatically be generalised to rainfed rice, different varieties, highly mechanised farms or irrigation schemes with substantially different institutional and agronomic conditions. This contextual boundary is a strength for internal comparability but a limitation for broad external validity.

CONCLUSION AND POLICY IMPLICATIONS

The study concludes that IR2793-80-1 paddy yield in Bunyala Irrigation Scheme is shaped by nonlinear and interdependent economic input relationships. Compared to the Cobb-Douglas model, the centred Translog model gave significantly better measure of the data, increasing explained variation in logged yield from 35.8% to 50.9% and improving both adjusted R^2 and information criteria. This is a clear indication that constant elasticities alone were insufficient to describe the sampled production relationships.

Fertiliser mattered through a nonlinear response, reinforcing the need for formulation-specific nutrient management rather than undifferentiated increases in product kilograms. Around the mean, farm size was positively associated with yield with a decreasing rate of return, reflecting that there were diminishing returns to increasing acreage, and it is advisable to expand acreage in proportion to available labour, nutrients, credit and irrigation capacity. Labour remained a positive and significant determinant at the mean input combination, supporting the importance of timely and well-organised farm operations. Productive credit was also positive and significant in the preferred Translog model as well and showed significant curvature, suggesting that the amount, timing, and productive use of credit is more informative than access to credit. Beyond these four objective-specific findings, the strong negative labour-credit interaction indicated that the inputs' contribution depended partially upon each other, which further underscores the importance of input management rather than stand-alone management.

For farmers and extension services, the main implication is to manage inputs as a coordinated package. Formulation, rate and timing of nutrients should be taken into account in nutrient recommendations. Labour plans should follow critical crop operations and planted acreage should reflect the resources available to manage it effectively. These findings can be put into simple language for extension rather than technical econometric terms: a formulation based nutrient guide; a seasonal labour calendar aligned to key rice operations, and a per-acre credit budgeting template that links borrowing to specific production needs. These tools can be presented to farmer groups, through co-operatives, and through local-language extension sessions to allow farmers who lack formal education to apply the evidence in real-world decisions. Such tools can be delivered through farmer groups, cooperatives and local-language extension sessions so that farmers with limited formal education can use the evidence in practical decisions. For financial institutions and cooperatives, production credit should be based on realistic per-acre budgets, released before critical activities and aligned with the rice production and marketing cycle. For irrigation-scheme and county-level policy, performance should be evaluated not only by acreage cultivated, physical fertiliser distributed or number of borrowers reached, but also by how effectively those resources combine to improve yield.

LIMITATIONS AND FURTHER RESEARCH

The study used cross-sectional, farmer-reported data from one rice variety, one irrigation scheme and one production season. While this provided greater internal comparability, it restricted external generalisation and did not allow for experimental causality to be determined. Unobserved soil fertility, water reliability, pest pressure, weather, extension contact and farmer's management ability are likely to be correlated with both input use and yield, which can lead to omitted-variable bias with the direction of the bias varying by input. Productive credit was modelled as the amount of borrowed funds actually used in production per acre; the model did not separately estimate the effects of credit source, borrowing cost, disbursement timing or cash-versus-in-kind delivery.

Furthermore, residual diagnostics showed some heteroscedasticity and tail departures, and the reported model did not contain an analysis using robust standard errors for HC1–HC3.Residual diagnostics also indicated tail departures and some heteroscedasticity, while the reported model did not include a separate HC1–HC3 robust-standard-error analysis. Finally, although the Translog model was supported by the hierarchical F-change test and lower AIC and BIC values, no cross-validation, bootstrap stability analysis or independent out-of-sample prediction was undertaken.

Future research should test the stability of the nonlinear relationships across multiple seasons, irrigation schemes and rice varieties; incorporate direct soil, water and pest measurements; and distinguish nutrient-specific responses rather than relying only on a composite nutrient measure. Credit research should examine whether the yield relationship varies by source, interest cost, disbursement timing and in-kind versus cash financing, while the labour-credit interaction should be tested against farmer management capacity and local labour-market conditions.

Time-invariant unobserved heterogeneity could be addressed using panel data, plausible endogeneity with valid instruments using instrumental-variable strategies, and field or quasi-experimental studies that are carefully designed to enhance causal interpretation. Future model validation should also consider heteroscedasticity-consistent standard errors, bootstrap stability and out-of-sample comparison of Cobb-Douglas and Translog specifications.

Declarations

Ethical Approval

The research study was approved by the institutional research team of Maseno University and was carried out within the framework of national research licensing. The participation was voluntary, informed consent was requested of respondents, personal identifiers were not included in analysis and reporting, and findings were reported in general terms.

Conflict of Interest

The authors declare that there is no conflict of interest.

Data Availability

The data supporting the findings of this study are available from the corresponding author upon reasonable request, subject to the confidentiality and ethical conditions under which the data were collected.

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