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Mathematical modelling of irrigation water requirements for rice farming in Central Thailand

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Abstract: Rice farming in Central Thailand relies heavily on controlled irrigation, making efficient water management critical for sustainable production. This study examines how production input costs influence irrigation water demand, measured as irrigation water volume per unit area ($m^3 \cdot ha^{-1}$), using panel data from 215 rice farmers in Sena District, Phra Nakhon Si Ayutthaya Province, covering the period 2016–2023. The dataset comprises 1,720 farm-year observations across approximately 7.58 km^2 of irrigated area. A log-linear Cobb–Douglas model estimated using panel regression techniques is applied to quantify the elasticities of irrigation water demand with respect to production input costs. Because all variables are expressed in logarithmic form, the estimated coefficients are directly interpretable as elasticities. The results indicate that fertiliser (β = 0.210), pesticide (β = 0.165), machinery (β = 0.302), and fuel costs (β = 0.128) have positive and statistically significant effects on irrigation water demand per rai, whereas seed and labour costs are not statistically significant. For example, a 1% increase in fertiliser expenditure is associated with a 0.21% increase in irrigation water demand per rai, holding other factors constant. The model explains a substantial share of the variation in irrigation water demand (R^2 = 0.63), indicating strong explanatory power. The findings highlight that chemical input use and mechanisation are key drivers of irrigation intensity in rice farming. These results underscore the importance of integrated water–input management strategies, including improved nutrient scheduling, energy-efficient pumping technologies, and data-driven irrigation planning, to enhance water-use efficiency and support sustainable rice production in Thailand.

Keywords: Cobb–Douglas model, irrigation water demand, mathematical modelling, panel data, rice farming

INTRODUCTION

Rice farming in Thailand relies heavily on irrigation. This is especially true in Central Thailand, where water availability is critical for crop productivity, farmers' income, and long-term agricultural sustainability (Carrijo, Lundy and Linquist, 2017; Wichaidist *et al.*, 2023). Rapid climatic variability, rising production costs, and increasing competition for water resources have intensified the need for effective irrigation planning. As a result, water management has become a major challenge for sustaining rice production systems that depend on controlled irrigation. In these systems, water application is actively regulated through canals, pumps, and scheduled delivery rather than relying only on rainfall (Ramsden, Wilson and Phrommarat, 2017). Recent evidence also indicates increasing variability in precipitation patterns. There is a rise in rainfall event frequency across many regions (Taking *et al.*, 2025).

In this study, irrigation water demand is defined as the actual volume of irrigation water applied per unit area (m^3 per rai[1]) at the farm level. This is observed from pumping records and irrigation delivery data. This concept reflects farmers' realised

[1] 1 rai = 1,600 m^2.

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irrigation behaviour under prevailing production and cost conditions. It differs from irrigation water requirements, which are modelled estimates based on crop evapotranspiration and climate, and from water-use efficiency, which relates crop yield to water input. Establishing these distinctions at the outset provides a clear conceptual basis for the analysis.

Previous studies have shown that irrigation water demand is closely associated with both biophysical and economic conditions. Irrigation decisions depend on crop type, soil moisture requirements, and water availability (Tuong and Bouman, 2003; Molden *et al*., 2007), while farm-level irrigation behaviour is also shaped by production input costs such as fertiliser, pesticide, machinery, labour, and fuel expenditures. In rice-based systems, higher moisture levels often require more intensive nutrient application and crop protection, and greater fertiliser and pesticide use tends to coincide with more intensive irrigation practices (Li *et al*., 2021; Shah *et al*., 2023). Mechanisation, including tractors, rotary tillers, and harvesting machinery, is commonly associated with more intensive growing cycles and more frequent water application (Cornish *et al*., 2004). Fuel costs also influence irrigation decisions, particularly in areas where diesel pumps remain the primary means of water extraction (Aggarwal *et al*., 2009).

In Thailand and many other Asian countries, irrigation water supplied through public schemes is often heavily subsidised or provided at very low cost. Under such institutional conditions, irrigation water demand may respond only weakly to water pricing because farmers face little or no direct cost for additional water use. Consequently, production input costs, rather than water prices, often become the more relevant determinants of irrigation behaviour. In rice-based farming systems, irrigation decisions are therefore more closely linked to fertiliser intensity, mechanisation, and energy use than to water pricing mechanisms (Wang *et al*., 2023; Chang, Benjamin and Sauer, 2024). This policy context is important for understanding irrigation water demand in canal-irrigated rice systems.

Although numerous studies have examined irrigation water demand, most have focused on macro-level water allocation, engineering-based estimates, crop–water requirement calculations, or simulation models. These approaches are essential for system design and basin-scale planning, but they often overlook actual farmer irrigation decisions and rarely incorporate comprehensive farm-level cost data. This has resulted in an underuse of farm-level information (Feike *et al*., 2017; Yu *et al*., 2025) and a limited understanding of how production costs shape actual irrigation water use in Thai rice farming. Recent studies have shown that integrated modelling approaches can improve understanding of water requirements under changing climate and management conditions (Sun *et al*., 2024), and that improved scheduling and field practices can substantially enhance water-use efficiency (Mayer *et al*., 2019). Nevertheless, empirical evidence quantifying the elasticity of farm-level irrigation water demand with respect to production input costs remains sparse in Thailand.

The Cobb–Douglas functional form has been widely used in agricultural economics to analyse production relationships and water demand because its log-linear specification allows estimated coefficients to be interpreted directly as elasticities. This modelling framework is particularly useful when working with agricultural data that may be limited or noisy (Christensen, Jorgenson and Lau, 1973; Li *et al*., 2021). In addition, panel data techniques improve estimation by capturing both time variation and cross-sectional variation (Gam and Rejeb, 2021). Recent research has further shown that mathematical and econometric modelling can provide valuable insights into irrigation water demand under varying climatic and management conditions, highlighting the importance of incorporating both economic and biophysical factors into water-demand analysis (Ahmad *et al*., 2021). Despite these advances, elasticity-based econometric analysis of irrigation water demand using farm-level panel data remains rarely applied in Thai rice farming.

Sustainable irrigation management also requires attention to how production costs influence farmers' decisions. Previous studies indicate that efficient water management is closely tied to input use because fertiliser, pesticide, and machinery application affects crop water needs (Cornish *et al*., 2004; Shah *et al*., 2023). In irrigation systems where water is subsidised, farmers' irrigation behaviour tends to respond more strongly to input cost structures than to water prices. Improved irrigation timing, field-level water management, and low-input production practices can reduce irrigation water demand while maintaining crop yields (Mayer *et al*., 2019; Putthidech *et al*., 2025a). These findings suggest that analysing the cost–water relationship is essential for developing more efficient and sustainable irrigation strategies.

This issue is particularly relevant to the Thai rice sector, where policy solutions must account for how farming expenses affect farmers' irrigation decisions. In systems where water demand shows little response to water charges, changes in fertiliser, pesticide, machinery, and fuel costs may have greater implications for irrigation intensity than direct water pricing. An elasticity-based approach can therefore help identify which production inputs most strongly influence irrigation water use and provide a basis for targeted policy interventions. Such interventions may include precision irrigation technologies, more energy-efficient pumping systems, and extension programmes that integrate nutrient and pest management with water conservation practices (Pathak *et al*., 2022; Hayatuddin *et al*., 2025; Pronti and Berbel, 2025). These considerations are especially important in irrigated rice-growing areas of Central Thailand, where water allocation policies and farm-level management decisions jointly determine the sustainability of rice production.

Sena District, in Central Thailand, is one of the important rice-growing areas in the region, covering approximately 7.58 km^2 (≈ 758 ha, i.e. 5,909 rai). Smallholder farmers in this area rely heavily on irrigation cycles, and understanding how production input costs affect irrigation water demand is therefore important for developing cost-effective irrigation plans and sustainable water-use policies (Kumar and Rajitha, 2019). Broader regional studies using remote-sensing evapotranspiration models have also shown that local irrigation practices can significantly influence basin-level water outcomes (Suwanlertcharoen *et al*., 2023). These characteristics make Sena District a suitable setting for examining the economic determinants of irrigation water demand under real farming conditions.

This study addresses an important research gap by applying a farm-level, elasticity-based econometric approach to panel data from rice farmers in Central Thailand. Specifically, it uses a log-linear Cobb–Douglas model to estimate how changes in seed, fertiliser, pesticide, labour, machinery, and fuel costs affect irrigation water demand (Putthidech *et al*., 2025a). While researchers have long studied irrigation efficiency and agricultural water management, few studies have measured how irrigation

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water demand responds to real multi-year production cost data in Thai rice farming, and no earlier work has applied a Cobb–Douglas cost-elasticity model with panel data to estimate the effects of production inputs on irrigation water demand in this context. By addressing this gap, the study provides new empirical evidence on the economic drivers of irrigation water demand and offers policy-relevant insights for precision irrigation strategies, input-efficient farming practices, and data-driven water management in Thailand's rice sector (Molle and Berkoff, 2007; Grafton, Williams and Perry, 2018; Gany, Sharma and Singh, 2019).

METHODS

STUDY AREA AND DATA COLLECTION

The study was conducted in Sena District, Phra Nakhon Si Ayutthaya Province, one of the rice-growing areas of Central Thailand. Field observations indicated that the district is situated on river plains. Because of its extensive canal network connected to the Chao Phraya River, rice farming relies heavily on managed water flows throughout each growing season. The total irrigated area in this study was approximately 7.58 km^2 (≈ 758 ha, i.e. 5,909 rai), distributed across the sub-districts of Hua Wiang, Ban Pho, Ban Phan, Ban Luang, and Sam Kor. Smallholder rice farming systems in these sub-districts follow similar cultivation calendars, while irrigation practices, input use, and cost structures vary across farms.

Data were collected from 215 rice farmers through a survey conducted from 2016 to 2023. The dataset records observations for each farmer, including seed, fertiliser, pesticide, labour, machinery, and fuel costs, as well as irrigation water demand. Irrigation water demand was measured in $m^3 \cdot rai^{-1}$. Water-use information came from two sources: (i) pump operating logs kept by farmers, which recorded irrigation hours and pump specifications, and (ii) irrigation service records from the irrigation authority, which were used to cross-check the pump logs. When direct meter readings were unavailable, pump discharge rates were used to convert operating hours into water-volume estimates for each farm.

Farmers were selected purposively with the assistance of agricultural officers to ensure that the farms represented typical irrigated rice systems in the district. The resulting dataset is a panel, with each farmer observed in every year of the study period. Before analysis, the data were cleaned, screened for outliers, and standardised to ensure comparability across years. This multiyear dataset provides a basis for analysing how changes in production input costs affect irrigation water demand under real farming conditions.

Several data limitations should be noted. Irrigation water demand could not be measured using sensor-based instruments; therefore, pump-operation logs were used as proxies for water extraction. The dataset does not include within-season irrigation phase information, such as tillering, booting, or panicle initiation, which prevents stage-specific modelling of water requirements. In addition, variables such as evaporation rates, groundwater depth, and micro-level rainfall variation at the farm scale were not available. These limitations do not reduce the validity of the analysis. In the authors' opinion, they indicate that the estimated elasticities mainly reflect economic rather than biophysical factors influencing irrigation behaviour.

PANEL DATA CONSTRUCTION AND SAMPLING

The empirical analysis is based on a balanced panel dataset consisting of 215 rice farmers observed annually from 2016 to 2023. The data provide eight years of information for each farm, yielding a total of 1,720 farm-year records. The model captures both differences between farmers and changes over time in growing conditions, input costs, and irrigation water demand patterns. Panel data were selected because irrigation water demand varies across households according to available water resources and across years due to changes in weather, costs, and irrigation schedules. The panel framework therefore captures both cross-farm differences and year-to-year changes in irrigation water demand and production input costs. It also reduces omitted-variable bias compared with single-year cross-sectional datasets.

Purposive sampling was used in conjunction with district agricultural officers to select farmers. The aim was to ensure that the sample represented irrigated rice-farming households in Sena District. The inclusion criteria required farmers in areas supplied by the district canal system to (i) grow rice in every season throughout the study period, (ii) keep records of production costs and irrigation practices, and (iii) remain active throughout the study period. This approach kept the observations complete and the dataset balanced by avoiding the loss of farmers.

Data cleaning and standardisation procedures were applied to prepare the panel for analysis. Missing values in input cost data were addressed by cross-verifying with agricultural extension records. Irrigation water estimates were harmonised by converting pump operation hours into volumetric units when direct meter readings were not available. These calculated values act as proxies for irrigation volume and remain consistent across farms because pump specifications from the irrigation authority are standardised. Converting variables into Thai Baht (THB, THB1 = USD0.03045, average exchange rate for 2025) per rai ensured comparability across households and over time.

Although the dataset has strengths, it also has limitations. Some irrigation water measurements are based on estimated discharge rather than metered volumes, which may introduce measurement error. Self-reported production costs may also contain recall errors. In addition, the data do not capture within-season changes in irrigation frequency. However, the longitudinal nature of the dataset helps reduce these problems by averaging errors over many years and allowing statistical methods to control for unobserved differences between farms.

Overall, the panel data construction and sampling strategy provide a basis for estimating the elasticity of irrigation water demand. They also support conclusions about how production input costs affect the irrigation behaviour of rice farmers in Central Thailand.

VARIABLES AND MODEL FRAMEWORK

Economic model

Irrigation water demand in rice production reflects farmers' decisions about combining inputs to achieve the desired output under financial and environmental constraints. Production intensity is influenced by fertiliser, pesticide, machinery, labour, and fuel costs. These inputs affect nutrient uptake, water loss, and soil moisture retention, which together determine crop water

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needs. Irrigation water demand therefore provides a basis for modelling water use as a relationship driven by production inputs. A general production technology can be expressed as:

$$Q = f(W, X_1, X_2, \dots, X_n) \tag{1}$$

where: Q = rice output, W = irrigation water, and X_i = production inputs.

Function f shown in Equation (1) increases in all arguments. The aim of the study is not to estimate output, but to examine how input intensity influences water demand. The production relationship can therefore be inverted conceptually:

$$W = g(X_1, X_2, \dots, X_n) \tag{2}$$

Function g increases with each X_i. Under the assumptions of production and unit elasticity of substitution, the water-demand function takes the Cobb–Douglas form:

$$\mathrm{W} \; = A \prod_{i=1}^{n} X_i^{\beta_i} \tag{3}$$

where: A = constant term, β_i = elasticity coefficient of irrigation water demand with respect to input X_i, and i = 1, 2, …, n, where n = the number of production input variables included in the model.

This means that changes in production input levels cause proportional changes in irrigation water demand. The partial derivative describing this mechanism is shown in Equation (4):

$$\frac{\partial W}{\partial X_i} = \beta_i A X_i^{\beta_i - 1} A \prod_{j \neq i}^{n} X_i^{\beta_i} \tag{4}$$

A positive β_i indicates that more intensive use of input X_i raises water requirements, consistent with agronomic theory. Taking natural logarithms yields the log-linear representation:

$$\ln W = \ln A + \sum_{i=1}^{n} \beta_i \ln X_i \tag{5}$$

The model can be directly estimated and provides elasticity-based interpretations of how production inputs affect irrigation water demand. Its mathematical structure establishes a clear link between the theoretical framework and the empirical data model.

Variable construction and measurement

Variable construction and measurement are presented in Table 1.

All financial variables were standardised to Thai Baht per rai to ensure comparability across farms with varying landholdings. Prior to estimation, all variables were transformed into natural logarithms to stabilise variance and enable elasticity-based interpretation of the estimated coefficients.

Because direct water meters were not available on all farms, irrigation water volume was subject to measurement uncertainty. Volumetric water use was therefore estimated by converting recorded pump operation hours into water volumes using irrigation authority records and standard pump discharge specifications. Potential measurement error may arise from variation in pump efficiency, maintenance conditions, or discrepancies between nominal and actual discharge rates.

This measurement error is expected to be largely random, as identical conversion procedures were applied consistently across farms and years. While random measurement error may attenuate coefficient magnitudes, it is unlikely to affect the direction of the estimated elasticities. The use of multi-year panel data, together with cluster-robust standard errors, further mitigates the influence of measurement noise on statistical inference. Consequently, despite data limitations, the estimated irrigation water demand elasticities can be interpreted as robust average responses under real-world farming conditions.

Model assumptions

The empirical model uses a log-linear Cobb–Douglas specification, which assumes that irrigation water demand and production input costs are multiplicatively related. After transformation, the

Table 1. Summary of variables

Variable	Description	Raw data source	Construction method[1)]	Unit
W	irrigation water demand (volume)	pump-meter logs; irrigation office records	$W = Q \cdot t_i$ (6) where: Q = discharge, t_i = irrigation hours; standardised by area	$m^3 \cdot rai^{-1}$
S	seed cost	farmer production logs	$S = SE / A$ (7) where: SE = annual seed expenditure, A = cultivated area	$THB \cdot rai^{-1}$ (current prices)
F	fertiliser cost	farmer production logs	$F = FE / A$ (8) where: FE = annual fertiliser expenditure	
P	pesticide cost	farmer production logs	$P = PE / A$ (9) where: PE = annual pesticide expenditure	
L	labour cost	farmer labour logs	$L = LE / A$ (10) where: LE = labour payments	
M	machinery cost	machinery rental/ ownership records	$M = ME / A$ (11) where: ME = annual machinery cost	
Fu	fuel cost	fuel purchase logs	$Fu = FUE / A$ (12) where: FUE = fuel cost for irrigation pumps and machinery	

[1)] All monetary variables are expressed in current Thai Baht (THB, THB1 = USD0.03045, average exchange rate for 2025) per rai (2025 price level) and were not adjusted for inflation.
Source: own study.

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model becomes linear in its parameters, allowing the coefficients to be interpreted as elasticities (Christensen, Jorgenson and Lau, 1973). The functional form also assumes constant elasticities and proportional responses. This specification is appropriate for agricultural production systems in which input–output relationships remain relatively stable (Chambers, 1988).

In order to ensure unbiasedness, ordinary least squares (OLS) estimation depends on a number of statistical assumptions, including linearity in parameters, the lack of perfect multicollinearity, and the zero conditional mean assumption, $E(\varepsilon_{it}/X_{it}) = 0$ (Wooldridge, 2010; Greene, 2018). In accordance with White (1980), cluster-robust standard errors are used because cost and irrigation data frequently show heteroskedasticity. The Breusch–Pagan Lagrange multiplier (LM) test (Breusch and Pagan, 1980) and Hausman test (Hausman, 1978) were used to assess the suitability of pooled, random-effects, or fixed-effects estimators because the panel structure introduces unobserved farmer-specific effects (Hsiao, 2022).

Measurement assumptions include the treatment of irrigation volume – obtained from pump logs or estimated discharge rates – as a consistent proxy for actual irrigation water demand (Molden *et al.*, 2007). To guarantee comparability between farms, all financial variables were converted to Thai Baht per rai.

Justification for the Cobb–Douglas production function

The Cobb–Douglas production function is useful because it provides a framework for modelling the relationship between irrigation water demand and production input costs. Its log-linear transformation allows the coefficients to be interpreted as elasticities, showing how changes in input expenditures affect irrigation water demand (Christensen, Jorgenson and Lau, 1973; Chambers, 1988). The form also works well with agricultural cost data because the log transformation stabilises variance and reduces heteroskedasticity (Wooldridge, 2010). In panel settings, the Cobb–Douglas specification retains its elasticity interpretation and supports the use of fixed-effects, random-effects, and robust OLS estimators (Hsiao, 2022). Because the study aims to measure how water demand changes with input costs, the Cobb–Douglas function provides a clear and policy-relevant model.

In comparison with more flexible functional forms such as the translog or constant elasticity of substitution (CES) specifications, the Cobb–Douglas form offers a parsimonious structure. This structure is particularly suitable for farm-level panel data with a moderate sample size. Flexible forms allow for variable elasticities and substitution patterns. However, they require the estimation of more parameters. This can reduce estimation efficiency and increase multicollinearity when applied to cost-based farm data.

The assumption of constant elasticities is appropriate in this study. This is because the objective is to estimate average proportional responses of irrigation water demand to changes in production input costs across farms and over time. The aim is not to capture nonlinear substitution effects. The unitary elasticity of substitution implied by the Cobb–Douglas model is also consistent with rice production systems in Central Thailand. In this region, inputs such as fertiliser, machinery, and fuel are typically applied in relatively fixed proportions. Cultivation practices and irrigation schedules determine these input proportions.

The Cobb–Douglas model provides a stable, clear way to estimate irrigation demand elasticities, while staying interpretable and relevant for policy analysis in irrigated rice systems.

ECONOMETRIC MODEL SPECIFICATION

The empirical model used in this study is based on a log-linear Cobb–Douglas form, which is appropriate for estimating the elasticity of irrigation water demand with respect to production input costs. In this specification, variables interact multiplicatively and become linear after logarithmic transformation, allowing the parameters to be interpreted directly as elasticities. This structure is well suited to agricultural water-demand studies because it provides a simple and interpretable framework that performs well under field conditions.

Irrigation water demand (W_{it}) is used as the dependent variable and is measured in cubic metres per rai. The explanatory variables are seed (S_{it}), fertiliser (F_{it}), pesticide (P_{it}), labour (L_{it}), machinery (M_{it}), and fuel costs (Fu_{it}), all measured in Thai Baht per rai. All variables were transformed using natural logarithms to reduce skewness and facilitate interpretation. The resulting econometric specification is given in Equation (13):

$$\ln W_{it} = \alpha_0 + \alpha_1 \ln S_{it} + \alpha_2 \ln F_{it} + \alpha_2 \ln F_{it} + \alpha_3 \ln P_{it} + \alpha_4 \ln L_{it} + \alpha_5 \ln M_{it} + \alpha_6 \ln Fu_{it} + \varepsilon_{it} \tag{13}$$

where: i = farm, t = year, α_0 = intercept, α_1–α_6 = estimated elasticity coefficients, ε_{it} = error term.

The model assumes constant elasticities, a linear relationship among the log-transformed variables, and distinct relationships among the independent variables. The error term ε_{it} is assumed to satisfy the standard OLS conditions, while heteroskedasticity and within-farm correlation are addressed using cluster-robust standard errors. The Breusch–Pagan LM test and Hausman test were used to determine whether pooled OLS, random-effects, or fixed-effects estimation was most appropriate for the panel data. The selected estimator matches the structural characteristics of the dataset. This specification provides a concise framework for analysing how production costs influence irrigation water demand in rice farming.

ESTIMATION METHOD

The log-linear Cobb–Douglas model was estimated using panel regression after logarithmic transformation of all variables, which allowed direct interpretation of the coefficients as elasticities. Two diagnostic tests were used to select the appropriate estimator for the panel dataset. First, the Breusch–Pagan LM test assessed whether unobserved farm-level heterogeneity was present in the data. The significant LM statistic indicated that pooled OLS was inappropriate and that a panel estimator should be used (Breusch and Pagan, 1980). Second, the Hausman specification test evaluated the choice between random-effects and fixed-effects estimation. The test result supported the use of the random-effects estimator (Hausman, 1978; Hsiao, 2022).

The Breusch–Pagan test was also used to assess heteroskedasticity. The significant χ^2 statistic ($p < 0.05$) indicated the presence of heteroskedasticity; therefore, cluster-robust standard errors were used to obtain reliable inference.

The panel structure of the dataset lets the model account for unobserved heterogeneity across farms by including farm-specific effects. These effects capture characteristics that do not change over time, such as soil conditions, irrigation infrastructure, and farmer management practices. Time effects were not explicitly modelled.

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The analysis mainly focuses on cross-farm and within-farm variation in production input costs, not on common macroeconomic or policy shocks that would affect all farms at once.

The choice of estimator used a two-step diagnostic procedure. First, the Breusch–Pagan LM test checked if unobserved farm-level effects were present. The significant LM test result argued against using pooled OLS estimation. This result showed that a panel data estimator was needed. Second, the Hausman specification test compared the consistency of fixed effects and random effects estimators. The non-significant Hausman statistic showed that unobserved farm-specific effects were not systematically correlated with the explanatory variables. This finding supported using the random-effects estimator as the more efficient choice.

The study uses a random-effects model with cluster-robust standard errors at the farm level. This approach addresses heteroskedasticity and within-farm serial correlation. The estimation strategy preserves both within and between farm variation in the data. The estimated coefficients represent average irrigation water demand elasticities across farms and over time. Using cluster-robust standard errors (CRSEs) also ensures reliable statistical inference without changing the economic meaning of the elasticity estimates.

All econometric analyses were performed using EViews Student Version 12, including panel-model diagnostics, heteroskedasticity testing, and robust standard error estimation. Cluster-robust standard errors at the farm level were applied to address heteroskedasticity and within-unit correlation, thereby improving the reliability of statistical inference (White, 1980; Cameron and Trivedi, 2005). Model adequacy was evaluated using R^2, adjusted R^2, and statistical tests of coefficient significance. These procedures supported the statistical and economic validity of the estimated relationships.

RESULTS AND DISCUSSION

DESCRIPTIVE STATISTICS

Descriptive statistics for the main production expenses in rice farming during 2016–2023 are presented in Table 2. The table reports the mean, standard deviation, minimum, and maximum values for each expense category.

Table 2. Descriptive statistics of the main production expenses for rice farming during 2016–2023

Variable	Mean	*SD*	Min.	Max.
Irrigation water demand	8,037	1,245	6,210	10,432
Seed cost	538.63	45.44	500	623
Fertiliser cost	957.13	74.61	880	1,097
Pesticide cost	884.88	74.99	824	1,027
Labour cost	632.00	52.51	588	734
Machinery cost	1,182.25	101.96	1,106	1,379
Fuel cost	590.38	50.85	559	697
Total cost	**4,848.69**	**393.58**	**4,458**	**5,557**

Note: *SD* = standard deviation.
Explanations: all cost variables are expressed in Thai Baht (THB, THB1 = USD0.03045, average exchange rate for 2025) per rai, and irrigation water demand is expressed in cubic metres per rai.
Source: own study.

Table 2 summarises descriptive statistics for irrigation water demand and production input costs for 215 rice farms observed from 2016 to 2023. The farms used an average of 8,037 $m^3 \cdot ha^{-1}$ of irrigation water, equivalent to 1,286 $m^3 \cdot rai^{-1}$, although water use varied substantially across farms. Input costs also showed different patterns of variation, with fertiliser, pesticide, and machinery expenses varying more than seed and labour costs. These differences provide a basis for examining the sensitivity of water use to economic factors in the following section.

MODEL RESULTS

Table 3 presents the regression results for the effects of production inputs on irrigation water demand among rice farmers in Central Thailand. The model explains the data well, with an R^2 of 0.63 and an adjusted R^2 of 0.59. These results indicate that variation in input intensity explains a substantial share of the observed variation in irrigation practices. The diagnostic statistics further support model adequacy: the Durbin–Watson statistic (1.87) indicates no serious autocorrelation, and the VIF values (1.95–3.45) remain within acceptable ranges, suggesting that multicollinearity is not a concern.

Table 3. Regression results

Variable	Coefficient (β)	*SE*	*t*-statistic	*p*-value
Constant (β_0)	2.913***	0.674	4.32	0.000
Seed cost (ln*S*)	–0.045	0.059	–0.76	0.450
Fertiliser cost (ln*F*)	0.210***	0.072	2.92	0.006
Pesticide cost (ln*P*)	0.165**	0.067	2.46	0.015
Labour cost (ln*L*)	–0.087	0.055	–1.58	0.118
Machinery cost (ln*M*)	0.302***	0.085	3.55	0.001
Fuel cost (ln*Fu*)	0.128**	0.060	2.13	0.035

Note: *SE* = standard error, R^2 = 0.63; adjusted R^2 = 0.59; *F*-statistic = 9.87; Durbin–Watson statistic = 1.87; *VIF* = 1.95–3.45; Breusch–Pagan LM test: $\chi^2(1)$ = 42.87, $p < 0.001$, Hausman test: $\chi^2(6)$ = 7.94, p = 0.241; Breusch–Pagan heteroskedasticity test: $\chi^2(1)$ = 16.42, $p < 0.0003$; *** = $p < 0.01$, ** $p < 0.05$.
Source: own study.

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The econometric model is supported by additional diagnostic tests. The Breusch–Pagan LM test produced a highly significant result (χ^2 = 42.87, p < 0.001), indicating that pooled OLS was inappropriate because the panel data contain unobserved characteristics that vary between farms. The Hausman specification test was non-significant (χ^2 = 7.94, p = 0.241), indicating no systematic difference between the fixed-effects and random-effects estimators and supporting the use of the random-effects model as the more efficient estimator. The Breusch–Pagan heteroskedasticity test yielded χ^2 = 16.42 (p = 0.0003), confirming that the residuals exhibit heteroskedasticity. Consequently, all coefficient estimates were computed using cluster-robust standard errors at the farm level to correct for non-constant variance and within-farm correlation. These checks confirm the structural soundness of the model and the reliability of the quantitative results.

The diagnostic results show that the panel structure is appropriate and that the random-effects estimator captures between-group variation effectively. In addition, the model retains its statistical power after correcting for heteroskedasticity, which supports the practical usefulness of the estimated elasticities.

The analysis shows that fertiliser cost has a positive and statistically significant elasticity of 0.21 (p = 0.006). This result is consistent with previous agricultural studies (Namara, Sally and Fraiture de, 2011; Ahsan *et al*., 2025). In practice, higher fertiliser use is often associated with greater irrigation intensity, as farmers apply more water to support input-intensive production. The relatively high elasticity suggests that irrigation demand in Thailand is closely linked to intensive production systems and established water-management practices.

Pesticide cost also shows a positive elasticity (β = 0.165, p = 0.015). Although pesticide use does not directly increase water demand through biological processes, farms with higher pesticide expenditure are often characterised by more intensive cultivation systems that require regular irrigation for crop protection and heat management. This pattern is consistent with findings from chemical-intensive rice-farming regions in Thailand and southern Laos (Baird *et al*., 2022). Overall, the results suggest that farms using larger amounts of production inputs tend to apply irrigation more intensively.

Machinery cost exhibits the highest elasticity (β = 0.302, p = 0.001), indicating that mechanisation is a key driver of irrigation intensity in Thailand's rice cultivation systems. In the Central Plains, tractors, power tillers, and water pumps are widely used for land preparation, levelling, and pumping operations. Mechanised farms tend to follow scheduled irrigation practices aligned with their production calendars, which can increase water use. The positive elasticity of fuel cost (β = 0.128, p = 0.035) supports this pattern, as farms in semi-irrigated and off-canal areas often rely on fuel-intensive pumping.

In contrast, seed cost (β = –0.045, p = 0.45) and labour cost (β = –0.087, p = 0.118) are not significant predictors of irrigation behaviour, which is consistent with the Thai agricultural context. Seed use varies little across farms because planting rates generally follow established practices rather than water conditions. Labour costs are also less closely related to pumping volume and irrigation timing in systems where mechanical operations dominate. These findings suggest that irrigation requirements in Thai rice systems are driven more by capital- and input-intensive operations than by labour costs or seeding rates (Naivinit *et al*., 2010).

In irrigated rice systems of Central Thailand, seeding rates are standardised and follow long-established agronomic norms. This leads to limited cross-farm variability in seed use. Therefore, differences in seed expenditure do not create meaningful differences in irrigation intensity.

In line with this, labour inputs are increasingly being replaced by mechanisation in key production stages, such as land preparation, transplanting, and irrigation pumping. Household labour and fixed-rate hiring arrangements further reduce the sensitivity of irrigation decisions to labour cost fluctuations, explaining the absence of a statistically significant relationship between labour expenditure and irrigation water demand.

These null effects, therefore, reflect structural characteristics of modern rice farming systems rather than model limitations, indicating that irrigation behaviour is primarily driven by capital- and input-intensive factors.

These findings are specific to canal-irrigated smallholder rice systems in Central Thailand. Here, irrigation is managed with controlled canal networks and pump-based delivery. As a result, the observed relationships may not apply to rainfed lowland rice, upland rice systems, or regions with different irrigation and farm structures.

The elasticity patterns offer several important insights for improving sustainable irrigation management. First, the strong influence of fertiliser, machinery, and fuel costs suggests that irrigation demand is highest in input-intensive production systems. Policymakers should therefore target these farms for precision irrigation technologies, such as moisture sensors, automated irrigation controllers, drip-in-furrow adaptations for rice, and variable-rate pumping systems. International evidence shows that such technologies can reduce irrigation water demand by 20–40% while maintaining yields (Molden *et al*., 2010), and they are highly applicable to the Central Region's pump-dependent rice systems. These policy implications are most relevant to canal-irrigated rice production areas in Central Thailand and should be applied with caution to other regions or production systems with different hydrological, institutional, or climatic conditions.

The estimated elasticities can be interpreted in terms of underlying biophysical and farm-management mechanisms. Higher fertiliser expenditures are associated with increased crop biomass and more intensive canopy development. These changes raise evapotranspiration demand and deplete soil moisture. Farmers respond to higher water demand by increasing irrigation frequency or volume. This explains the positive elasticity between fertiliser costs and irrigation water demand.

The strong elasticity of machinery costs reflects management-driven factors rather than just technical ones. Investments in machinery are often linked to higher cropping intensity, more precise land levelling, and increased pumping capacity. These investments enable more frequent or timely irrigation. Mechanised farms, as a result, tend to apply greater volumes of irrigation water to support intensive production schedules.

Fuel cost elasticity also captures the energy–water nexus in pump-dependent irrigation systems. Higher fuel expenditures indicate greater pumping activity. This is especially true in areas relying on groundwater or off-canal supplies. Increased pumping leads directly to increased irrigation water extraction.

The analysis shows that water consumption depends heavily on machinery and fuel use, highlighting the need for pump-

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efficiency policies that promote high efficiency electric pumps and solar-powered pumping systems, alongside improved monitoring through local water governance mechanisms. The findings are particularly relevant for canal-irrigated areas such as Ayutthaya and Pathum Thani, where intensive groundwater pumping poses risks to long-term aquifer sustainability. However, these implications should not be interpreted as representative of all Thai rice-growing regions, especially those dominated by rainfed production or alternative irrigation arrangements.

These elasticity-based insights point to several concrete and feasible policy interventions in the Thai context. First, targeted programs to improve irrigation pump efficiency – such as subsidies or credit schemes for replacing outdated diesel pumps with high-efficiency electric or solar-powered pumps – can directly reduce water extraction while lowering fuel costs for farmers.

Second, extension programs that jointly optimise fertiliser application and irrigation scheduling can help farmers avoid excessive watering following fertiliser use. Training that integrates nutrient management with moisture monitoring would reduce unnecessary irrigation while maintaining yields, particularly in input-intensive rice systems.

Third, targeted support for moisture-based irrigation scheduling, including the adoption of simple soil-moisture sensors or alternate wetting and drying (AWD) practices, can enable farmers to better align irrigation timing with actual crop water needs. Such interventions are especially suitable for Central Thailand, where canal infrastructure and pump-based systems are already in place.

Together, these targeted measures align irrigation management policies with the cost-sensitive decision-making processes revealed by the estimated elasticities, enhancing both water-use efficiency and economic sustainability in irrigated rice farming.

Farmers can reduce operating costs through nutrient and irrigation management systems that also lower water use. Extension agencies should provide training on fertiliser timing and moisture control to help farmers avoid excessive irrigation after fertiliser application, which appears to occur frequently in the study area.

The final policy implication is that interventions should focus on high-elasticity inputs. Labour and seed costs do not significantly affect irrigation decisions in this context. As a result, broad water-saving programs that do not differentiate are likely less effective. Building on this, policies informed by empirical elasticity estimates and tailored to specific irrigation systems can improve water governance, enhance irrigation system performance, and encourage greater farmer participation.

Evidence from empirical studies and contextual analysis indicates that Thailand needs sustainable irrigation supported by economic incentives, behavioural change, and technological improvement. The findings suggest practical approaches to improve water distribution efficiency and reduce pumping activity in support of sustainable rice production systems.

CONCLUSIONS

This study estimated a Cobb–Douglas irrigation water demand model to analyse how production input costs shape farmers' irrigation behaviour in the Central Region of Thailand. Machinery cost showed the highest elasticity (0.302), followed by fertiliser (0.210) and pesticide (0.165), indicating that capital- and chemical-intensive production systems account for a substantial share of irrigation water use. The results further show that fertiliser, pesticide, machinery, and fuel costs influence irrigation practices, whereas seed and labour costs do not. Overall, the elasticity patterns suggest that Thai rice farmers use irrigation intensity to support input-intensive and mechanised production systems rather than labour allocation or seeding rates.

These findings offer robust insights for canal-irrigated smallholder rice systems in Central Thailand. Use caution when applying these results to other rice systems or regions. The estimated elasticities may not directly apply to rainfed lowland rice, upland rice, or areas with different irrigation, climate, or farm structures. Future studies should test whether similar cost–water links exist in other production and hydrological contexts.

Three key policy insights emerge. First, farmers with high fertiliser and chemical use should be targeted with precision-irrigation measures, including soil-moisture monitoring, automated irrigation systems, and integrated nutrient and water management plans. Second, the strong effects of machinery and fuel costs highlight the need to support energy-efficient pump technologies and pumping regulations that can reduce groundwater extraction. Third, extension programmes focused on integrated water and nutrient management may help farmers reduce water use while maintaining production.

The study has several limitations. It relies on cost-based proxies for production intensity, which do not fully capture biophysical characteristics such as soil texture, water retention, and microtopography. In addition, water-use measurements were based on farmer-reported and estimated pumping volumes, which may contain measurement error. The model also assumes a fixed functional form and does not account for adjustment between planting seasons.

Future studies should combine remote-sensing-based evapotranspiration data with spatial variation in soil characteristics and high-frequency sensor records of irrigation activity. The model could also be extended to include stochastic weather patterns, risk behaviour, and nonlinear production relationships to improve predictive performance. Comparative research across irrigation and rainfed systems and across different Thai rice-growing areas would help develop irrigation management plans suited to specific regions.

This research provides scientific evidence to support the development of irrigation policies that combine technological and economic approaches in Thailand's rice production system.

AUTHOR CONTRIBUTIONS

1st Author (contribution – 55%): study design, data collection, statistical analysis, data interpretation, manuscript preparation, and literature search. 2nd Author (contribution – 15%): data collection, manuscript preparation, and literature search. 3rd Author (contribution – 15%): study design, data collection, manuscript preparation, and literature search. 4th Author (contribution – 15%): study design, data collection, manuscript preparation, and literature search.

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DATA AVAILABILITY STATEMENT

On request, research data can be obtained.

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CONFLICTS OF INTEREST

The authors did not disclose any potential conflicts of interest.

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