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Estimation of Price and Substitution Elasticities of Cotton Production Inputs: Empirical Evidence from Baghlan Province, Afghanistan

Hafizullah Radmand[1, 2], Ali Keramatzadeh[1*], Ramtin Joolaei[1], and Farshid Eshraghi[3]

Abstract

Cotton serves as an important crop that supplies numerous products for human use and supports a wide range of industrial applications. This study aims to estimate the price and substitution elasticities among the production inputs of cotton in Baghlan Province, Afghanistan. Data were collected through 132 questionnaires, using stratified random sampling from cotton growers in the province. The relationships among production inputs were examined using a translog cost function in conjunction with the Seemingly Unrelated Regression (SUR) approach. The results showed that the price elasticities of demand for land, animal manure, phosphate fertilizer, urea fertilizer, seeds, labor, water, and machinery were -0.036, -0.815, -0.056, -0.050, -0.056, -0.092, -0.074, and -0.198, respectively. All price elasticities of input demand were less than one, indicating inelastic demand, that is, input use is not highly sensitive to price changes. The cross elasticities of demand for inputs were also less than one, confirming inelastic demand across all inputs. The small values of substitution elasticities further indicated that policies targeting a single input would have little impact on the allocation of other inputs. Therefore, it is recommended that policymakers avoid focusing on individual inputs and instead consider all inputs as an integrated system when designing agricultural policies.

Keywords: Allen and Morishima Elasticities of Substitution, Cost Function, Demand for Inputs, Seemingly Unrelated Regressions (SUR).

Introduction

Cotton is a vital global crop and a significant economic driver, especially in developing nations. Often referred to as "white gold," it is the world's most consumed natural fiber and a cornerstone of the textile industry (Khan et al., 2020). Globally, cotton is cultivated on more than 32.5 million hectares, with a total production of 24.08 million tons in 2021 (Tokel et al., 2022). The industry

[1] Department of Agricultural Economics, Faculty of Agricultural Management, Gorgan University of Agricultural Science and Natural Resources, Gorgan, Islamic Republic of Iran.
[2] Department of Agricultural Economics and Extension, Baghlan University, Baghlan, Afghanistan.
[3] Department of Agricultural Economics, Faculty of Agriculture, College of Agriculture and Natural Resources, University of Tehran, Karaj, Islamic Republic of Iran.
*Corresponding author, email: alikeramatzadeh@gau.ac.ir or alikeramatzadeh@yahoo.com

provides livelihoods for approximately 31.5 million farmers and employs around 150 million people worldwide (FAO, 2021).

In Afghanistan, cotton has been an important crop since 1921. Before the 1979 revolution, the country maintained a strong cotton industry, cultivating 128,000 hectares and producing 150,000 tons annually. However, political instability led to a sharp decline in cultivation. Since 2002, the Afghan Ministry of Agriculture has prioritized reviving the sector, contributing to a resurgence in agricultural production. By 2019, the area under cotton cultivation had reached 36,000 hectares, with a total production of 14,000 tons across various provinces, including Baghlan, where farmers produced 4,620 tons from 1,650 hectares (Radmand et al., 2021).

Understanding the economics of production is fundamental to ensuring the long-term sustainability of any industry. According to Surya et al. (2021), comprehensive knowledge of production costs and factor contributions is vital for improving efficiency, enhancing competitiveness, and fostering sustainable growth. In agriculture, effective resource management remains a cornerstone of development, especially given the limited availability of key production inputs in many regions (Adom & Adams, 2020).

Analyzing the demand for production inputs requires assessing their sensitivity to price changes and understanding the relationships between them (Rey et al., 2023). This analysis is essential to inform policy decisions. If inputs are complementary, reducing costs necessitates proportionally reducing all inputs. However, if inputs are substitutes, producers can lower overall production costs and increase profits by replacing more expensive inputs with cheaper alternatives (Ren et al., 2021). The extent to which inputs can substitute for one another plays a key role in determining the economic impacts of policies targeting input demand. (Feng et al., 2025).

Furthermore, analyzing input costs provides valuable policy insights for improving resource allocation efficiency and enhancing farmers' productivity (Du et al., 2019). Elasticities are key parameters in this analysis, as they reveal how the relative cost share of production factors changes with price fluctuations (Bellocchi & Travaglini, 2023). According to Binswanger (1974), studying the elasticity of substitution is fundamental to understanding how easily or with difficulty one production factor can be replaced by another. A higher elasticity indicates greater ease of substitution. In this context, the present study estimates the price and substitution elasticities of cotton production inputs in Afghanistan's Baghlan Province, offering important insights into the interrelationships among these factors.

In Afghanistan, the absence of provincial-level studies has significant implications for agricultural policy. National averages conceal substantial regional variation in resource endowments, production systems, and market access. As a result, policies designed from aggregated national data often fail to address the distinct challenges and opportunities within specific provinces. For instance, a uniform fertilizer subsidy or mechanization program may be effective in some areas but economically infeasible or environmentally unsustainable in others. Provincial-level analyses, such as this study in Baghlan, are therefore essential to develop locally adapted policies that enhance productivity, ensure equitable resource distribution, and improve farmers' livelihoods. Accordingly, this study seeks to answer the following research question: What are the price and substitution elasticities among the production inputs used in cotton farming in Afghanistan's Baghlan Province, and what are the implications of these relationships for regional agricultural policy and resource allocation?

Numerous studies have utilized the seemingly unrelated regression (SUR) method and the translog cost function to analyze input demand and factor relationships. For example, Deininger et al. (2018) investigated substitution effects within Swiss manufacturing firms and identified a complementary relationship between capital and energy, particularly in energy-intensive sectors. In the agricultural context, Du et al. (2019) estimated the price and substitution elasticities for peach and cherry production in Beijing, China, and found that labor serves as a substitute for land, fertilizers, and pesticides. Similarly, Pippa Rochelle & Ferreira Filho (1999) investigated the cotton input market in São Paulo, Brazil, and revealed that labor and machinery were complementary inputs, while other factor pairs showed substitution relationships.

The substitutability and complementarity of inputs often vary by context and crop. For instance, Pang et al. (2021) observed a complementary relationship between fertilizer and labor in corn production in China, whereas a substitutive relationship was identified in cabbage cultivation. Their findings further indicated that the price elasticity of fertilizer demand was inelastic in both production systems. Similar results have been reported in other studies, highlighting the generally inelastic nature of demand for agricultural inputs. Ansari Roshandeh et al. (2022) found that water demand for rice production in Iran's Gorgan County was inelastic, indicating that significant price increases would not substantially reduce water consumption. Koç and Karayiğit (2022) analyzed the Australian water market and the impact of electricity price liberalization, finding that electricity demand was relatively price-sensitive and that electricity complemented both labor and capital.

Forgenie et al. (2023) reported that in Indonesia, the demand for animal feed exhibited greater responsiveness to variations in income than to fluctuations in price. Landolsi and Miled (2024) reached a similar conclusion regarding energy demand in Tunisia, noting that its sensitivity to income was greater than to price fluctuations. Wang and Wu (2025) examined modernization and substitution elasticities in China's grain production using a Translog production function. Their results reveal complementary relationships among several key factor pairs, including capital–fertilizer, capital–land, fertilizer–land, pesticide–land, and fertilizer–labor. In contrast, substitutive relationships were identified for capital–pesticide, fertilizer–pesticide, pesticide–labor, and land–labor. Similarly, Gu et al. (2025) investigated how rising rural labor prices influence land use patterns and crop allocation by applying the Translog function. Their findings indicate that higher labor costs have reduced the planted area of rice and maize, while significantly increasing the area devoted to wheat. This shift is primarily driven by factor substitution, specifically, the replacement of labor with fertilizer and machinery, which has been instrumental in reshaping cropping patterns. These results underscore the importance of developing and promoting labor-saving technologies, such as more efficient fertilizers and small-scale agricultural machinery.

Collectively, these studies highlight the importance of analyzing input demand and factor relationships to inform effective resource management and policy. However, despite the global significance of cotton and the well-established methodologies for this type of analysis, a notable research gap exists in Afghanistan. To the best of current knowledge, no comparable research has been undertaken at the provincial level, particularly in Baghlan, a major agricultural region. Hence, this study seeks to fill this gap by estimating the price and substitution elasticities of cotton production inputs in Baghlan Province, Afghanistan, thereby generating valuable insights to support local agricultural development.

Study Area

Afghanistan, with an area of 652,864 square kilometers, is divided into 34 provinces and 398 districts, based on its administrative divisions (Fig. 1). As of 2020, its population was approximately 38.8 million. Approximately 61.6% of the population relies on agriculture and animal husbandry, and the agricultural sector accounts for 23% of the GDP (Radmand et al., 2021). Afghanistan possesses an estimated 75 billion cubic meters of total annual freshwater resources, comprising roughly 57 billion cubic meters (76%) of surface water and 18 billion cubic meters

(24%) of groundwater (Mahmoodi, 2008). Baghlan Province is one of the major industrial and agricultural regions located in northeastern Afghanistan (Fig. 1). The province covers 21,118 square kilometers and has an estimated population of about 1.77 million people (Radmand et al., 2021).

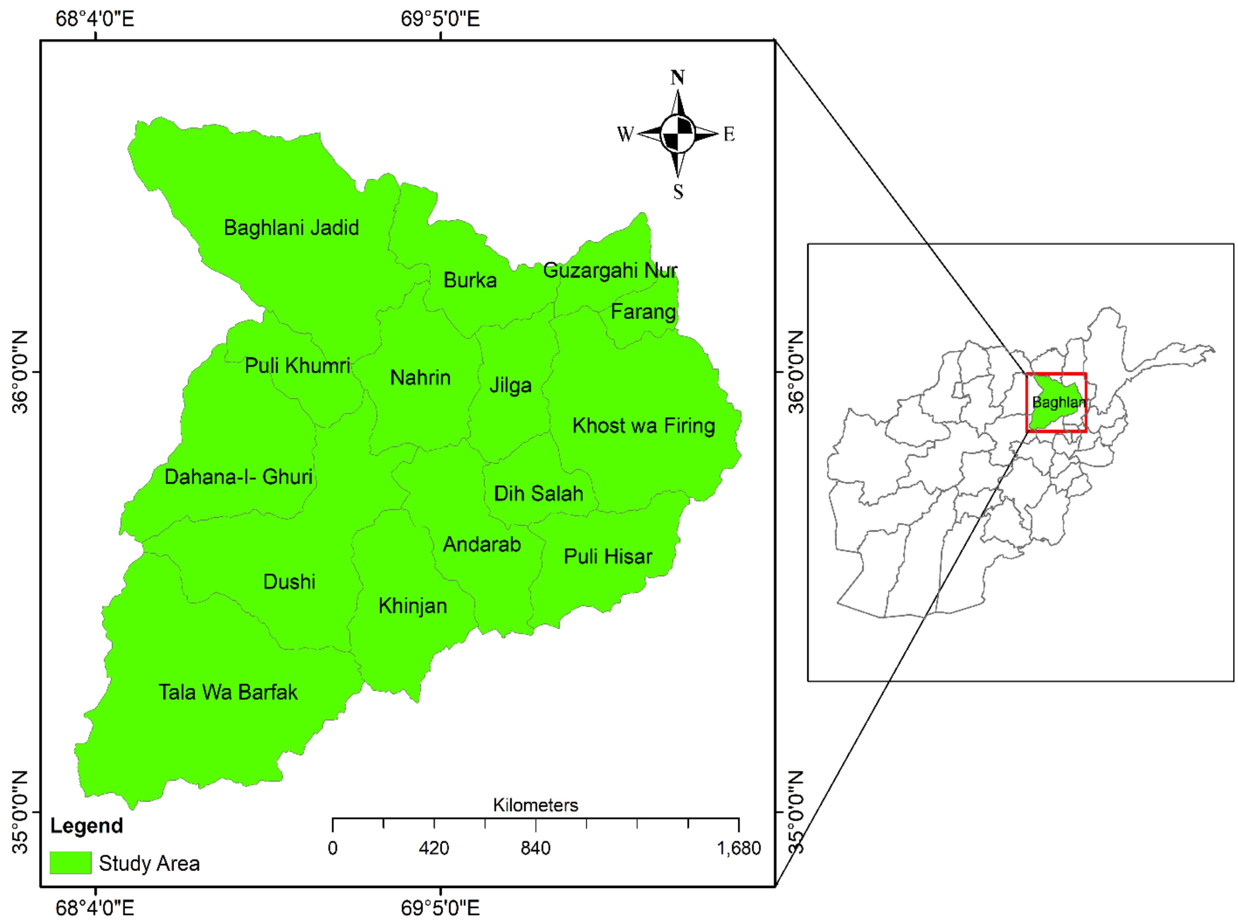

Figure 1. The Geographic Location of Baghlan Province in Afghanistan.

Data and Methods

This study estimated the input demand function to determine the price elasticity of demand and the elasticities of substitution among production inputs. Consistent with previous research (Du et al., 2019; Miljkovic et al., 2016; Mufutau Opeyemi, 2021; Rey et al., 2023; Ren et al., 2021; Ranjbar et al., 2023), the Seemingly Unrelated Regression (SUR) approach was employed, as it is well-suited to cross-sectional data and effectively accounts for the interdependence among input demand equations. By considering the contemporaneous correlation among the error terms across equations within the system, the Seemingly Unrelated Regression (SUR) method yields more efficient parameter estimates compared to the single-equation Ordinary Least Squares (OLS) approach. Since changes in prices or external shocks simultaneously affect the demand for all inputs, SUR enables the modeling of such interdependence. Consequently, SUR is a powerful tool for accurately estimating price and substitution elasticities within a system of equations (Griffin et al., 1987; Du et al., 2019). The general form of the Seemingly Unrelated Regression (SUR) model is as follows (Griffin et al., 1987):

$$Y_{1i} = \alpha_1 + \beta_1 X_{1t} + u_{1t} \qquad ; \quad t = 1, \dots \dots T \tag{1}$$

$$Y_{2i} = \alpha_2 + \beta_2 X_{2t} + u_{2t} \qquad ; \quad t = 1, \dots \dots T \tag{2}$$

Here, (Y) represents the level of production, and (X) denotes the production factor. While Equations (1) and (2) may appear independent, certain underlying factors can cause them to vary simultaneously, affecting production outcomes through the disturbance terms (u_{1t}) and (u_{2t}). Consequently, this study utilized the Seemingly Unrelated Regression (SUR) method to estimate both the translog cost function and the input share demand functions.

Translog Production Function

The translog production function was proposed by Christensen et al. (1972). This function is a logarithmic, flexible functional form that allows substitution elasticities and partial production elasticities to vary with input levels (Debertin, 2012). The translog production function encompasses all three production regions, permitting marginal products to be increasing, decreasing, or even negative. Beyond the primary variable coefficients, the translog specification also estimates the interaction terms between variables. The general form of the translog production function is presented in Equation (3) (Griffin et al., 1987).

$$\mathrm{Ln}(Y) = \alpha_0 + \sum_{i=1}^{n} \alpha_0 \,\mathrm{Ln}(\alpha_i) + \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} b_{ij} \,\mathrm{Ln}(x_i)\,\mathrm{Ln}(x_j) \tag{3}$$

Where Y represents the production amount, and x_i and x_j are the production inputs.

Translog Cost Function

The cost function describes the relationship between total cost, input prices, and the level of output. Deriving the cost function involves either minimizing total cost for a specified level of production or maximizing output within a given budget constraint. As the dual of the production function, each production function corresponds to a unique cost function, allowing the production function to be inferred from the cost function. Equation 4 shows the general form of the cost function.

$$C= f\ (P_1, P_2, P_3, \dots, P_n, Q) \tag{4}$$

Where C represents the total cost, Q represents the amount of production, and P_1 to P_n represent the prices of production inputs.

This study utilized the Translog cost function to estimate the cost structure of production. A key advantage of this functional form is that the substitution elasticities among production factors are not constant but vary depending on both the production level and the combination of inputs used (Griffin et al., 1987). This functional form has been widely used in economic literature (Christensen & Ramananantoandro, 1971; Koç & Karayiğit, 2022). One key reason for its widespread application is the ease of interpreting results and deriving marginal costs (Johansen, 1972). The general form of the translog cost function is given by Equation (5):

$$\begin{aligned} \ln(C) = \alpha_0 &+ \sum_{i=1}^{n} \alpha_i \ln Y_i + \sum_{i=1}^{n} \beta_i \ln P_i \\ &+ \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \alpha_{ij} \ln Y_i \ \ln Y_j \\ &+ \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \beta_{ij} \ln P_i \ \ln P_j + \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \gamma_{ij} \ln Y_i \ \ln P_j + e_i \end{aligned} \tag{5}$$

Where C represents the total cost, Y_i represents the level of production, P_i and P_j represent the prices of inputs, and α_i, β_i, α_{ij}, β_{ij}, and γ_{ij} denote the estimated parameters. In general, the Translog cost function possesses the properties of positivity, symmetry, and homogeneity with respect to input prices. The dependent variable of the translog function is expressed in logarithmic form, ensuring the positivity condition. The restriction $\beta ij = \beta ji$ must be imposed to ensure symmetry. The assumption of homogeneity with respect to input prices implies that if all input prices double while output remains constant, the total cost will also double. To satisfy the homogeneity condition of the cost function, the following constraints must be imposed when estimating the SUR model (Garcia & Randall, 1994; Rigi & Shahraki, 2016):

$\sum_{i=1}^{n} \beta_i = 1 \qquad \sum_{i=1}^{n} \beta_{ij} = \sum_{j=1}^{n} \ \beta_{ji} = 0$

Demand functions of inputs

There are two primary approaches to deriving the demand function for input. When the production function displays increasing returns to scale (IRS), the input demand function is obtained by minimizing the cost function. In this scenario, differentiating the cost function with respect to input prices (Shephard's Lemma) produces an indirect (conditional) input demand function. Conversely, if the production function exhibits decreasing returns to scale (DRS), the input demand function can be derived through profit maximization using Hotelling's Lemma. The general form of the conditional demand function of production inputs, according to Shephard's theorem, which represents the equations of the cost share of inputs, is given by Equation (6):

$$S_i = \frac{P_i X_i}{\sum P_i X_i} = \frac{P_i}{C}.X_i = \frac{P_i}{C}.\frac{\partial C}{\partial P_i} = \frac{\partial \ln C}{\partial \ln P_i} = a_i + \sum_{j=1}^{n} \beta_{ij} \ln P_j + \gamma_{iy} \ln Y \quad (6)$$

Here, S_i denotes the cost share of the i_{th} input, Crepresents the total production cost, P_i and P_j denote the prices of the ith and j_{th} inputs, respectively, and $Y$is the output level. Because the cost function satisfies the adding-up condition $(\sum_{i=1}^{n} S_i = 1)$, only $n-1$ cost share equations are linearly independent, and the input prices are expressed in relative terms in the main function. The standard procedure for estimating input demand functions involves omitting one cost share equation from the system of simultaneous equations and estimating the parameters for the remaining $n-1$ equations. The parameters of the omitted equation are subsequently derived from the estimated parameters of the included equations (McGeehan,1993; Pippa Rochelle & Ferreira Filho, 1999; Shahraki & AliAhmadi, 2014; Wijetunga, 2015; Rigi & Shahraki, 2016; Ning et al., 2020, and Abbasian et al., 2022). Therefore, one cost share equation, typically corresponding to the input with the lowest cost share, is omitted from the model. In this study, the cost of pesticides was excluded from the analysis because it represented the smallest share of the total production cost. Therefore, the cost function of each production input was estimated as follows:

$$SS = \alpha S + \beta_{SS}\, Log\left(\frac{PS}{PP}\right) + \beta_{SL} Log\left(\frac{PL}{PP}\right) + \beta_{SR}\, Log\left(\frac{PR}{PP}\right) + +\beta_{SN}\, Log\left(\frac{PN}{PP}\right) +$$
$$\beta_{SPH} Log\left(\frac{PPH}{PP}\right) + \beta_{SA} Log\left(\frac{PA}{PP}\right) + \beta_{SW}\, Log\left(\frac{PW}{PP}\right) + \beta_{SM}\, Log\left(\frac{PM}{PP}\right) + \gamma_{SY} Log\, Y \quad (7)$$

$$SL = \alpha L + \beta_{LS}\, Log\left(\frac{PS}{PP}\right) + \beta_{LL} Log\left(\frac{PL}{PP}\right) + \beta_{LR}\, Log\left(\frac{PR}{PP}\right) + \beta_{LN}\, Log\left(\frac{PN}{PP}\right) +$$
$$\beta_{LPH} Log\left(\frac{PPH}{PP}\right) + \beta_{LA} Log\left(\frac{PA}{PP}\right) + \beta_{LW}\, Log\left(\frac{PW}{PP}\right) + \beta_{LM}\, Log\left(\frac{PM}{PP}\right) + \gamma_{LY} Log\, Y \quad (8)$$

$$SN = \alpha N + \beta_{NS}\, Log\left(\frac{PS}{PP}\right) + \beta_{NL} Log\left(\frac{PL}{PP}\right) + \beta_{LR}\, Log\left(\frac{PR}{PP}\right) + \beta_{NN}\, Log\left(\frac{PN}{PP}\right) +$$
$$\beta_{NPH} Log\left(\frac{PPH}{PP}\right) + \beta_{NA} Log\left(\frac{PA}{PP}\right) + \beta_{NW}\, Log\left(\frac{PW}{PP}\right) + \beta_{NM}\, Log\left(\frac{PM}{PP}\right) + \gamma_{NY} Log\, Y \qquad (9)$$

$$SPH = \alpha PH + \beta_{PH\,S}\, Log\left(\frac{PS}{PP}\right) + \beta_{PH\,L} Log\left(\frac{PL}{PP}\right) + \beta_{PHR}\, Log\left(\frac{PR}{PP}\right) + \beta_{PH\,N}\, Log\left(\frac{PN}{PP}\right) +$$
$$\beta_{PH\,PH} Log\left(\frac{PPH}{PP}\right) + \beta_{PH\,A} Log\left(\frac{PA}{PP}\right) + \beta_{PH\,W}\, Log\left(\frac{PW}{PK}\right) + \beta_{RM}\, Log\left(\frac{PM}{PP}\right) + \gamma_{PH\,Y} Log\, Y \qquad (10)$$

$$SR = \alpha R + \beta_{RS}\, Log\left(\frac{PS}{PP}\right) + \beta_{RL} Log\left(\frac{PL}{PP}\right) + \beta_{RR}\, Log\left(\frac{PR}{PP}\right) + \beta_{RN}\, Log\left(\frac{PN}{PP}\right) +$$
$$\beta_{R\,PH} Log\left(\frac{PPH}{PP}\right) + \beta_{R\,A} Log\left(\frac{PA}{PP}\right) + \beta_{R\,W}\, Log\left(\frac{PW}{PP}\right) + \beta_{RM}\, Log\left(\frac{PM}{PP}\right) + \gamma_{R\,Y} Log\, Y \qquad (11)$$

$$SW = \alpha W + \beta_{WS}\, Log\left(\frac{PS}{PP}\right) + \beta_{WL} Log\left(\frac{PL}{PP}\right) + \beta_{WR}\, Log\left(\frac{PR}{PP}\right) + \beta_{WN}\, Log\left(\frac{PN}{PP}\right) +$$
$$\beta_{W\,PH} Log\left(\frac{PPH}{PP}\right) + \beta_{WA} Log\left(\frac{PA}{PP}\right) + \beta_{WW}\, Log\left(\frac{PW}{PP}\right) + \beta_{WM}\, Log\left(\frac{PM}{PP}\right) + \gamma_{W\,Y} Log\, Y \qquad (12)$$

$$SA = \alpha R + \beta_{AS}\, Log\left(\frac{PS}{PP}\right) + \beta_{AL} Log\left(\frac{PL}{PP}\right) + \beta_{AR}\, Log\left(\frac{PR}{PP}\right) + \beta_{AN}\, Log\left(\frac{PN}{PP}\right) +$$
$$\beta_{A\,PH} Log\left(\frac{PPH}{PP}\right) + \beta_{A\,A} Log\left(\frac{PA}{PP}\right) + \beta_{A\,W}\, Log\left(\frac{PW}{PP}\right) + \beta_{AM}\, Log\left(\frac{PM}{PP}\right) + \gamma_{R\,Y} Log\, Y \qquad (13)$$

$$SM = \alpha M + \beta_{MS}\, Log\left(\frac{PS}{PP}\right) + \beta_{ML} Log\left(\frac{PL}{PP}\right) + \beta_{MR}\, Log\left(\frac{PR}{PP}\right) + \beta_{MN}\, Log\left(\frac{PN}{PP}\right) +$$
$$\beta_{M\,PH} Log\left(\frac{PPH}{PP}\right) + \beta_{MA} Log\left(\frac{PA}{PP}\right) + \beta_{MW}\, Log\left(\frac{PW}{PP}\right) + \beta_{MM}\, Log\left(\frac{PM}{PP}\right) + \gamma_{M\,Y} Log\, Y \qquad (14)$$

In these equations, S_a, S_s, S_l, S_n, S_{ph}, S_p, Sw, S_r, and S_m represent the cost shares of manure, seed, labor, nitrogen, phosphate, pesticide, water, land, and machinery, respectively. Similarly, P_a, P_s, P_l, P_n, P_{ph}, P_p, Pw, P_r, and P_m denote their corresponding input prices.

Allen-Uzawa Partial Elasticities of Substitution (AES)

In empirical research, the most commonly employed measures of input substitution are the Allen–Uzawa Elasticities of Substitution (AES) (Zha & Ding, 2014), which were initially proposed by Hicks and Allen (1934) and subsequently refined by Allen (1938) and Uzawa (1962). Partial elasticities are a useful method for measuring the substitutability between factors of production and play an essential role in determining the optimal composition and efficient utilization of production inputs (Stern, 1997). These elasticities measure the percentage change in the ratio of two production inputs in response to a one-percent change in their relative prices. A positive Allen Elasticity of Substitution (AES) signifies that the inputs function as substitutes, whereas a negative

AES indicates a complementary relationship between them (Knoblach & Stöckl, 2020). Equations (15) and (16) specify the Allen cross- and own-partial elasticities of substitution.

$$AES_{ij} = \frac{\beta_{ij} + S_i S_j}{S_i S_j} \quad (15)$$

$$AES_{ii} = \frac{\beta_{ii} + S_i (S_i - 1)}{S_i^2} \quad (16)$$

Here, AES_{ij} represents Allen's cross-partial elasticity of substitution, AES_{ij} denotes Allen's own-partial elasticity of substitution, β_{ij} is the coefficient of the j[th] input in the equation for the i[th] input, and s_i and s_j are the cost shares of the i[th] and j[th] inputs, respectively. The signs of these elasticities are typically expected to be negative, reflecting the general inverse relationship between the demand for a product and its price, except in the case of Giffen goods. Allen's cross-partial elasticities are symmetric; if $AES_{ij} > 0$, this indicates a substitutive relationship between the two inputs, whereas $AES_{ij} < 0$ indicates a complementary relationship (Kuroda, 1987).

Own and Cross-Price Elasticity of Input Demand

The own-price elasticity of demand for a production input reflects the percentage change in the quantity demanded of that input resulting from a one-percent change in its own price. Likewise, the cross-price elasticity of demand measures the percentage change in demand for one input resulting from a one percent change in the price of another input (Zha & Ding, 2014). In the present study, cross-price elasticities of input demand are employed to analyze the substitutive or complementary relationships among production inputs. These elasticities were computed using Equations (17) and (18).

$$\varepsilon_{ii=AES_{ii} * S_i} \quad \text{for } i = j \quad (17)$$

$$\varepsilon_{ij=AES_{ij} * S_j} \ . \ \varepsilon_{ji=AES_{ji} * S_i} \quad \text{for } i = j \quad (18)$$

Here, $\boldsymbol{\varepsilon_{ii}}$ denotes the own-price elasticity of demand, $\boldsymbol{\varepsilon_{ij}}$ represents the cross-price elasticity of demand for the i[th] input with respect to the price of the j[th] input, AES_{ij} indicates Allen's cross-partial elasticity of substitution, and AES_{ii} denotes Allen's own-partial elasticity of substitution. When the price elasticity of input demand is greater than zero ($\varepsilon_{ii} > 0$), the demand for that input is considered elastic; when it is less than zero ($\varepsilon_{ii} < 0$), the demand is inelastic; and when it equals unity ($\varepsilon_{ii} = 0$), the demand demonstrates unitary elasticity. Similarly, when the cross-price elasticity of input demand is positive ($\varepsilon_{ij} > 0$), the inputs are considered substitutes, whereas a negative value ($\varepsilon_{ij} < 0$) indicates that the inputs are complements. It is important to note that, unlike the

Allen Elasticity of Substitution, these elasticities are asymmetric—meaning that the elasticity of demand for the i^{th}input with respect to the price of the j^{th} input is not necessarily equal to that of the j^{th}input with respect to the price of the i^{th}input ($\varepsilon_{ij} \neq \varepsilon_{ji}$).

The cross-price elasticity of input demand measures the absolute degree of substitution between inputs but does not capture the relative substitution among production factors (Zha & Ding, 2014). In contrast, Allen's cross-partial elasticity of substitution (AES), compared with the cross-price elasticity of input demand, reflects the relative substitutability between two factors while accounting for the substitution effects of other inputs (Stern, 1997).

The Morishima Elasticity of Substitution (MES)

The Morishima Elasticity of Substitution (MES) is defined as the logarithmic derivative of the ratio of input quantities with respect to the ratio of their prices (Morishima, 1967). Introduced by Morishima in 1967, this measure serves as an alternative approach to assessing the degree of substitutability among production inputs.

While the Allen–Uzawa Elasticity of Substitution (AES) fails to retain several essential characteristics of the original Hicksian concept—specifically, (i) it does not accurately measure the ease of substitution or the curvature of the isoquant, (ii) it offers no insight into relative factor shares, and (iii) it cannot be formulated as the logarithmic derivative of an input quantity ratio with respect to a price ratio—Morishima introduced the Morishima Elasticity of Substitution (MES) to overcome these limitations.

The Morishima elasticity of substitution is defined as follows:

$$MES_{ij} = \varepsilon_{ij} - \varepsilon_{jj} \tag{18}$$

Where $\boldsymbol{\varepsilon}_{ij}$ represents the cross-price elasticity of the *i*th input demand with respect to the *j*th input price, $\boldsymbol{\varepsilon}_{jj}$ represents the own-price elasticity of demand for the *j*th input, and MES denotes the Morishima elasticity of substitution. A positive MES value indicates a substitution relationship between two inputs, and the magnitude of the value determines the strength of this relationship. Values greater than one (MES > 1) denote strong substitution, whereas values between zero and one (0 < MES ≤ 1) indicate weak substitution. Conversely, a negative MES value signifies a complementary relationship, where the absolute magnitude reflects the degree of complementarity—values greater than one (|MES| > 1) suggest strong complementarity, and values between zero and one (0 < |MES| ≤ 1) indicate weak complementarity. Overall, the MES results are consistent with the Allen–Uzawa partial elasticity estimates, reinforcing the robustness and coherence of the empirical findings.

Results and Discussion

The results of this study include a descriptive analysis of cotton farmers' data, the estimation of the translog cost function and input share demand functions, and the calculation of the Allen, Morishima, own-price, and cross-price elasticities of demand.

Table 1. Results of Descriptive Statistics for Cotton Farmers in Baghlan Province,

Variable	Unit	Mean	Minimum	Maximum	Standard Deviation
Age	years	44.9	20	80	12.97
Education	years	6.6	0	16	6.39
Family size	persons	10.9	5	26	3.97
Experience	years	15.3	2	42	5.93
Animal Manure	kg/hectare	0.9	0	5	1.45
Phosphate Fertilizer	kg/hectare	190	100	290	58.08
Urea Fertilizer	kg/hectare	178	100	250	28.30
Seed	kg/hectare	76.5	62	98	8.70
Herbicide	kg/hectare	0.9	0	3	0.95
Insecticide	kg/hectare	0.6	0	3	0.88
Fungicide	kg/hectare	0.3	0	3	0.71
Labor	person-days	164.9	133	192	12.77
Water	cubic meters/hectare	4386.1	2433	6272	867
Machinery	hours	23.5	17	30	3.18

Source: Research Findings.

Based on the descriptive statistics, the average cotton farmer in Baghlan province is a seasoned practitioner, with an average of 15.3 years of experience, despite a relatively low average education level of 6.6 years. The data highlight a high reliance on family labor, with a large average family size of 10.9 and a substantial labor input of 164.9 person-days per hectare. This contrasts sharply with the limited use of machinery (23.5 hours per hectare), confirming the labor-intensive nature of cotton cultivation. Furthermore, the results reveal a strong dependency on chemical fertilizers, with high average application rates for both phosphate and urea. In contrast, the use of animal manure is exceptionally low and highly variable, indicating that it is not a primary input source for most farmers. Overall, these findings provide a crucial foundation for understanding the economic behavior and production constraints of farmers in the region.

Estimation Results of the Cost Function

Table 2 presents the estimation results of the translog cost function for cotton production in Baghlan province, Afghanistan. As shown, the total cost of cotton production depends on the prices of land, animal manure, nitrogen fertilizer, phosphate fertilizer, pesticides, labor, water, and machinery. While individual coefficient interpretations in Translog models are complex due to the presence of numerous interaction terms, they are primarily used here to derive elasticity estimates, which offer more interpretable insights into the relationships among production inputs.

Table 2. Results of the Translog cost function of cotton in Baghlan province, Afghanistan.

Variables	Description	Coefficients	Prob.	VIF
C	Intercept	6.4317	0.0000	
Log(PA)	Logarithm of the Animal manure price	0.0032	0.0172	3.14
Log(PS)	Logarithm of Seed price	0.0207	0.0000	1.69
$\text{Log}(\text{PA})^2$	Square logarithm of animal manure price	0.0009	0.0000	4.46
$\text{Log}(\text{P}L)^2$	Square logarithm of labor wage	0.1176	0.0000	3.55
$\text{Log}(\text{P}N)^2$	Square logarithm of nitrogen price	0.0158	0.0111	1.81
$\text{Log}(\text{P}P)^2$	Square logarithm of pesticide price	0.0003	0.0000	2.53
$\text{Log}(\text{P}PH)^2$	Square logarithm of phosphate price	0.0293	0.0000	4.07
$\text{Log}(\text{P}R)^2$	Square logarithms of the land price	0.1043	0.0000	1.07
$\text{Log}(\text{P}W)^2$	Square logarithms of water price	0.0009	0.0000	1.71
Log(Y)* Log(PL)	Interaction of production and labor price	-0.0570	0.0000	4.87
Log(Y)* Log(PM)	Interaction of production and machinery price	0.0662	0.0000	4.96
Log(PA)* Log(PPH)	Interaction of animal manure price and phosphate price	-0.0003	0.0049	4.28
Log(PA)* Log(PW)	Interaction of animal manure price and water price	0.0003	0.0209	4.49
Log(PL)* Log(PN)	Interaction of labor wage and nitrogen price	-0.0212	0.0254	3.90
Log(PL)* Log(PR)	The interaction of labor wage and land price	-0.1396	0.0000	4.25
Log(PM)* Log(PP)	Interaction of machinery and pesticide price	0.0001	0.0000	1.70
Log(PM)* Log(PPH)	Interaction of machinery price and phosphate price	-0.0265	0.0000	4.03
Log(PM)* Log(PR)	The interaction of machinery price and land price	-0.0196	0.0096	3.85
Log(PPH)* Log(PR)	Interaction of phosphate price and land price	-0.0198	0.0000	2.98
R^2	0.9992			
Adjusted R^2	0.9991			
F-Statistics	8088.11			
Prob. (F-statistics)	0.0000			

Source: Research Findings.

In this study, we employed the Variance Inflation Factor (VIF) test to assess multicollinearity (O'Brien, 2007), the Jarque-Bera test to examine the normality of disturbance terms, the White test to diagnose heteroscedasticity, and the LM test to detect autocorrelation. The results are presented in Tables 2 and 3. The VIF test indicates that there is no serious multicollinearity in the model, as all values are well below the standard threshold of 5. Furthermore, the results of the Jarque–Bera test indicate that the null hypothesis of normally distributed residuals cannot be rejected (Prob > 0.05). Similarly, the results of the White and LM tests confirm that the null hypotheses of homoscedasticity and no autocorrelation in the disturbances cannot be rejected (Prob > 0.05).

Table 3. Test results of normality, heteroscedasticity, and autocorrelation in the translog cost function of cotton.

Test	Normality (Jarque-Bera Statistics)	Heteroskedasticity (White Test)	Autocorrelation (LM-Test)
T-Statistics	4.3222	0.4267	1.3205
Prob.	0.1151	0.9821	0.2712

Source: Research Findings

Estimation Results of Input Demand Functions Using Seemingly Unrelated Regression Equations (SURE)

Table 4 presents the estimated demand functions for cotton inputs in Baghlan province, Afghanistan. These functions were systematically estimated using the Seemingly Unrelated Regression Equations (SURE) method, and the results were subsequently used to calculate the elasticities of substitution, as described previously.

Table 4. Results of estimating the demand functions of the share of inputs in cotton production in the Baghlan province of Afghanistan.

Inputs	α	$\beta_{PR\,PR}$	$\beta_{PR\,PA}$	$\beta_{PR\,PPH}$	$\beta_{PR\,PN}$	$\beta_{PR\,PS}$	$\beta_{PR\,PL}$	$\beta_{PR\,PW}$	$\beta_{PR\,PM}$	γ_{PRY}
Land	0.288 (6.75)*	0.208 (15.1)	-0.0004 (-10.1)	-0.024 (-19.5)	-0.0097 (-5.51)	-0.004 (-2.19)	-0.131 (-33.7)	-0.004 (-2.91)	-0.033 (-11.1)	-0.007 (-1.42)
	α	$\beta_{PA\,PR}$	$\beta_{PA\,PA}$	$\beta_{PA\,PPH}$	$\beta_{PA\,PN}$	$\beta_{PA\,PS}$	$\beta_{PA\,PL}$	$\beta_{PA\,PW}$	$\beta_{PA\,PM}$	γ_{PAY}
Animal manure	0.0671 (1.20)	-0.003 (-1.89)	-0.001 (21.79)	-0.001 (-0.53)	0.004 (-1.51)	0.0005 (0.182)	-0.003 (-0.60)	0.001 (0.83)	-0.0001 (-0.03)	-0.003 (-0.49)
	α	$\beta_{PPH\,PR}$	$\beta_{PPH\,PA}$	$\beta_{PPH\,PPH}$	$\beta_{PPH\,PN}$	$\beta_{PPH\,PS}$	$\beta_{PPH\,PL}$	$\beta_{PPH\,PW}$	$\beta_{PPH\,PM}$	γ_{PPHY}
Phosphate	0.185 (5.89)	-0.023 (-17.0)	-0.0001 (-5.82)	0.070 (76.14)	-0.004 (-2.96)	-0.002 (-1.31)	-0.034 (-12.0)	0.0004 (0.40)	-0.006 (-2.84)	-0.002 (-0.62)
	α	$\beta_{PN\,PR}$	$\beta_{PN\,PA}$	$\beta_{PN\,PPH}$	$\beta_{PN\,PN}$	$\beta_{PN\,PS}$	$\beta_{PN\,PL}$	$\beta_{PN\,PW}$	$\beta_{PN\,PM}$	γ_{PNY}
Nitrogen	0.096 (12.36)	-0.009 (-43.5)	-0.000 (-4.89)	-0.002 (-10.6)	0.030 (88.8)	-0.0006 (-1.75)	-0.013 (-18.2)	-0.0002 (-0.97)	-0.004 (-8.02)	-0.0003 (-0.37)
	α	$\beta_{PS\,PR}$	$\beta_{PS\,PA}$	$\beta_{PS\,PPH}$	$\beta_{PS\,PN}$	$\beta_{PS\,PS}$	$\beta_{PS\,PL}$	$\beta_{PS\,PW}$	$\beta_{PS\,PM}$	γ_{PSY}
Seed	0.064 (12.36)	-0.007 (-48.7)	-0.000 (-5.95)	-0.001 (-10.9)	-0.001 (-5.66)	0.020 (80.2)	-0.008 (-18.0)	-0.0002 (-1.29)	-0.005 (-4.30)	0.0007 (1.30)
	α	$\beta_{PL\,PR}$	$\beta_{PL\,PA}$	$\beta_{PL\,PPH}$	$\beta_{PL\,PN}$	$\beta_{PL\,PS}$	$\beta_{PL\,PL}$	$\beta_{PL\,PW}$	$\beta_{PL\,PM}$	γ_{PLY}
Labor	0.079 (1.90)	-0.1295 (-11.1)	-0.0005 (-13.3)	-0.032 (-26.5)	-0.015 (-8.54)	-0.013 (-6.80)	0.243 (64.0)	-0.005 (-3.72)	-0.046 (15.8)	0.008 (1.78)
	α	$\beta_{PW\,PR}$	$\beta_{PW\,PA}$	$\beta_{PW\,PPH}$	$\beta_{PW\,PN}$	$\beta_{PW\,PS}$	$\beta_{PW\,PL}$	$\beta_{PW\,PW}$	$\beta_{PW\,PM}$	γ_{PWY}
Water	0.036 (8.46)	-0.002 (-20.4)	-0.000 (-3.26)	-0.0005 (-4.33)	-0.0003 (-1.68)	-0.000 (-0.22)	-0.0042 (-10.7)	0.008 (58.39)	-0.0008 (-2.94)	0.0001 (0.31)
	α	$\beta_{PM\,PR}$	$\beta_{PM\,PA}$	$\beta_{PM\,PPH}$	$\beta_{PM\,PN}$	$\beta_{PM\,PS}$	$\beta_{PM\,PL}$	$\beta_{PM\,PW}$	$\beta_{PM\,PM}$	γ_{PMY}
Machinery	0.160 (11.15)	-0.031 (-78.5)	-0.0001 (-7.38)	-0.007 (-17.8)	-0.002 (-4.36)	-0.002 (-3.56)	-0.042 (-32.4)	-0.0008 (-1.81)	0.087 (87.71)	0.002 (1.75)

Source: Research Findings * Numbers in parentheses are t-statistics...

The statistical significance of the coefficients was assessed at the 5% level, with p-values less than 0.05 considered statistically significant. Table 4 shows that all the coefficients of the demand function for the land cost share are significant at this level, except for the production variable. The demand for land share is positively related to the price of land; that is, as the price of land increases, the share of land in the total cost of cotton production also rises. In contrast, there is a significant negative relationship between the prices of animal manure, phosphate fertilizer, nitrogen fertilizer, seed, labor, water, and machinery, indicating that as the prices of these inputs increase, the share of land in total cost decreases. The demand functions for other input shares can be interpreted similarly.

Results of the Allen-Uzawa Partial Elasticities of Substitution (AES)

Table 5 presents the results of Allen–Uzawa's own and cross partial elasticities of substitution, calculated from the estimated coefficients of the demand functions. All the Allen–Uzawa partial elasticities of substitution (i.e., the diagonal elements of the elasticity matrix) have the expected negative sign, reflecting the inverse relationship between the price of an input and its quantity demanded, consistent with economic theory. The results indicate a mix of elastic and inelastic relationships. The absolute magnitude of the substitution elasticity is elastic (greater than one) for animal manure (-99.08), water (-9.302), seeds (-2.508), machinery (-1.659), and nitrogen fertilizer (-1.49), suggesting that changes in the relative prices of these inputs would lead to more than proportional changes in their usage. In contrast, the elasticity is inelastic (less than one) for phosphate fertilizer (-0.692), labor (-0.221), and land (-0.109), indicating that the demand for these inputs is relatively insensitive to price changes. The high elasticity of animal manure suggests that its consumption is highly responsive to price fluctuations, making it a viable input for rapid adjustments in production. Conversely, the low elasticity of land implies that its use is relatively stable and not significantly affected by price changes, reflecting its fundamental role as a fixed factor of production.

Table 5. Partial elasticity of the Allen-Uzawa substitution for cotton production inputs in Baghlan province, Afghanistan.

Inputs	Land	Manure	Phosphate	Nitrogen	Seed	Labor	Water	Machinery
Land	-0.109	0.831	0.090	0.122	0.078	0.033	0.057	-0.031
Manure	--	-99.080	0.725	0.858	0.831	0.811	0.764	0.885
Phosphate	--	--	-0.692	0.067	0.283	0.073	0.431	-0.249
Nitrogen	--	--	--	-1.490	0.197	0.057	0.868	-0.492
Seed	--	--	--	--	-2.508	-0.267	3.567	0.719
Labor	--	--	--	--	--	-0.221	-0.923	0.751
Water	--	--	--	--	--	--	-9.302	1.358
Machinery	--	--	--	--	--	--	--	-1.659

Source: Research Findings

The cross-elasticity results provide deeper insights into the relationships among inputs. Land exhibits a complementary relationship with machinery (AES =-0.031), indicating that expanding cultivated area requires additional machinery. This finding partially aligns with Bui et al. (2018), who observed similar factor substitutions in rice production in Vietnam. The results also reveal a weak substitution relationship between land and most other inputs, including manure, fertilizers, seeds, and labor. These findings support the theory of agricultural intensification in developing economies, as confirmed by Hussain et al. (2020), where labor and other inputs are utilized to increase yield per unit of land.

Animal manure serves as a substitute for all other inputs, including phosphate, nitrogen, seeds, labor, water, and machinery. This notable finding supports sustainable agricultural practices. The capacity to replace chemical inputs, such as phosphate and nitrogen fertilizers, with animal manure presents an opportunity to mitigate environmental externalities and reduce chemical pollution.

Both phosphate and nitrogen fertilizers exhibit a substitutable relationship with seeds, labor, and water, suggesting that increased use of labor, for instance, could reduce the need for fertilizers, with positive environmental implications. In contrast, both fertilizers show a complementary relationship with machinery, likely because the application of fertilizers depends on machinery, so greater use of one input requires greater use of the other.

Labor is a complement to seeds (AES =-0.267) and water (AES =-0.923). The complementarity with seeds indicates that cotton cultivation in this region is labor-intensive, particularly during the manual sowing process. The complementarity with water suggests that traditional irrigation methods require a significant amount of manual labor. Labor is also a substitute for machinery (AES =0.751). This finding is consistent with economic theory and aligns with studies by Zhan and Zhou (2019), but contrasts with Pippa Rochelle and Ferreira Filho (1999), who found a complementary relationship between these inputs in Brazil. The positive elasticity indicates that an increase in machinery prices would lead to increased labor usage, and vice versa, confirming the potential for substituting manual labor for mechanical power.

Water is a complement to labor but a substitute for all other inputs. The complementarity with labor reflects the reliance on traditional irrigation methods, which require substantial manual effort. The substitution relationship with other inputs suggests that increased use of these inputs, such as higher-quality seeds or additional fertilizers, can enhance productivity and lead to more efficient water use.

Seeds exhibit a substitution relationship with water and machinery, indicating that the use of higher-quality seeds can reduce the need for these inputs. However, they are complementary to labor, emphasizing the traditional, labor-intensive sowing practices in the region.

Results of Morishima Elasticity of Substitution (MES)

Table 6 reports the Morishima Elasticities of Substitution (MES) among the primary cotton production inputs in Baghlan Province. Each cell in the table displays the MES value for the input listed in the row in response to a price change in the input listed in the corresponding column. For instance, the value in cell row 1, column 2, represents the elasticity of substitution of land with respect to manure following a change in the price of manure. The results indicate that most input pairs exhibit positive MES values, implying varying degrees of substitution between them. The strongest substitution occurs between manure and other inputs, particularly labor (MES = 1.146), land (MES = 1.081), and phosphate fertilizer (MES = 0.870). These values suggest that animal manure can effectively replace part of the chemical fertilizer demand, and increased labor use can complement organic input management, reflecting both economic and environmental advantages. Similarly, machinery shows moderate substitution relationships with labor (MES = 0.510), seed (MES = 0.214), and water (MES = 0.209), indicating that mechanization can partly substitute for manual operations and input handling. In contrast, the negative MES values between water and other inputs—especially labor (MES = -0.457), manure (MES = -0.068), and land (MES = -0.055)—indicate complementarity. This pattern reflects traditional irrigation systems that rely heavily on manual labor and land expansion. Overall, the MES estimates reveal that substitution is generally stronger among organic and chemical inputs and weaker between resource-intensive factors like water and labor. These findings are broadly consistent with the Allen–Uzawa elasticity results, confirming similar substitution and complementarity patterns across key input pairs.

The results of the Morishima Elasticities of Substitution (MES) in this study are broadly consistent with findings from previous research. Similar to Du et al. (2019), who reported limited substitution possibilities among major agricultural inputs in fruit production, our results indicate weak substitution between labor and machinery and strong substitution between organic and chemical fertilizers. Likewise, Pang et al. (2021) found that substitution patterns vary by crop type, with fertilizer and labor being substitutes in some contexts and complements in others, a pattern also observed in our study. The complementary relationship between water and labor in Baghlan province aligns with the findings of Ansari Roshandeh et al. (2022) for irrigated rice production in Iran, highlighting the persistence of labor-intensive irrigation practices in developing agricultural systems. In contrast, the strong substitution between animal manure and chemical fertilizers found in our analysis extends previous results, suggesting that organic inputs could play a larger role in sustainable cotton production. Overall, these comparisons confirm the reliability of the MES estimates and demonstrate that the substitution and complementarity relationships identified in this study are consistent with international evidence.

Table 6. Morishima elasticity of substitution for cotton production inputs in Baghlan province, Afghanistan.

Inputs	Land	Manure	Phosphate	Nitrogen	Seed	Labor	Water	Machinery
Land	--	0.042	0.043	0.040	0.038	0.050	0.036	0.033
Manure	1.081	--	0.870	0.839	0.830	1.146	0.817	0.900
Phosphate	0.086	0.062	--	0.059	0.063	0.087	0.060	0.032
Nitrogen	0.081	0.050	0.048	--	0.047	0.072	0.050	-0.007
Seed	0.083	0.063	0.080	0.063	--	-0.054	0.085	0.129
Labor	0.103	0.098	0.098	0.094	0.086	--	0.085	0.168
Water	-0.055	-0.068	-0.039	-0.045	0.006	-0.457	--	0.063
Machinery	0.188	0.204	0.178	0.181	0.214	0.510	0.209	--

Source: Research Findings

Results of Own- and Cross-Price Elasticities of Input Demand

Table 7 presents the own- and cross-price elasticities of demand for cotton production inputs in Baghlan province, Afghanistan. All price elasticities of demand for land, animal manure, phosphate fertilizer, nitrogen fertilizer, seeds, labor, water, and machinery exhibit the expected negative sign, in line with economic theory. The absolute values of the own-price elasticities are less than one for all inputs, indicating that demand is inelastic. These results are partially consistent with Wijetunga (2023), who analyzed rice production in Sri Lanka. In practical terms, a one percent increase in input prices leads to a less than one percent decrease in input demand. Among the inputs, animal manure has the highest own-price elasticity, while land has the lowest.

Table 7. Domestic and intersecting price elasticities of demand for cotton production inputs in Baghlan province of Afghanistan.

Demand Function \ Inputs	Land	Manure	Phosphate	Urea	Seed	Labor	Water	Machinery
Land	-0.036	0.007	0.007	0.004	0.002	0.014	0.000	-0.003
Manure	0.271	-0.815	0.059	0.029	0.019	0.337	0.006	0.089
Phosphate	0.029	0.006	-0.056	0.002	0.006	0.030	0.003	-0.025
Urea	0.040	0.007	0.005	-0.050	0.004	0.031	0.007	-0.050
Seed	0.025	0.007	0.023	0.007	-0.056	-0.111	0.029	0.072
Labor	0.011	0.007	0.006	0.002	-0.006	-0.092	-0.007	0.076
Water	0.019	0.006	0.035	0.029	0.080	0.383	-0.074	0.137
Machinery	-0.010	0.007	-0.020	-0.016	0.016	0.312	0.011	-0.198

Source: Research Findings

Table 7 presents the own- and cross-price elasticities of demand for production inputs. These elasticities indicate how the demand for each input responds to a one percent change in the price of other inputs. In terms of complementarity and substitution, the results are consistent with the Allen–Uzawa partial elasticities of substitution.

Conclusions

This study analyzed the price and substitution elasticities of cotton production inputs in Baghlan Province, Afghanistan, using a translog cost function estimated through the Seemingly Unrelated Regression (SUR) method. The findings revealed that the demand for all production inputs—land, labor, fertilizers, water, seeds, manure, and machinery—is inelastic, indicating that changes in input prices have only a limited effect on input use. Among the inputs, animal manure exhibited the highest own-price elasticity, suggesting its potential role as a flexible input for cost adjustments, whereas land showed the lowest elasticity, reflecting its fixed nature in the production process.

The Allen–Uzawa and Morishima elasticity estimates further highlighted the interrelationships among production inputs. Strong substitution relationships were observed between animal manure and chemical fertilizers, while labor and machinery demonstrated weak substitution, confirming limited potential for replacing human labor with mechanization. Conversely, labor and water displayed complementary relationships, reflecting the persistence of traditional irrigation systems that require intensive manual effort.

These findings have several policy implications. Promoting the use of animal manure can help reduce dependency on chemical fertilizers, lower production costs, and mitigate environmental impacts. However, mechanization policies should be implemented cautiously, as the substitution between machinery and labor may lead to job displacement in rural areas. Policymakers should therefore consider integrated agricultural development strategies that simultaneously enhance productivity, maintain employment, and support environmental sustainability.

Finally, although the Seemingly Unrelated Regression (SUR) method provides efficient estimates by accounting for correlations among input demand equations, it has certain limitations. The model does not incorporate potential dynamic effects or unobserved heterogeneity among farms, which could influence input demand behavior. Although this study provides valuable insights into input demand and substitution elasticities that can inform policy design, it does not directly assess the welfare impacts of specific policy scenarios on producers. Future research could build upon these findings by incorporating welfare or simulation models to evaluate how changes in input prices, subsidies, or technology adoption influence producer income and resource allocation.

References

1. Adom, P. K., & Adams, S. (2020). Decomposition of technical efficiency in agricultural production in Africa into transient and persistent technical efficiency under heterogeneous technologies. *World Development*, *129*, 104907.
2. Ansari Roshandeh, S., Keramatzadeh, A., Rezaee, A., and Ghorbani, K. (2022). Estimation of Water Demand Function in Rice Production in Gorgan County: Application of the Seemingly Unrelated Regression (SUR) Method. *Journal of Agricultural Economics Research*, *14*(2).
3. Aytop, Y., Sahin, Z., & Akbay, C. (2022). Economic efficiency of cotton production in Turkey. *Custos e* Agronegocio on line, *18*(2), 104-122
4. Bellocchi, A., and Travaglini, G. (2023). Can variable elasticity of substitution explain changes in labor share? *Journal of Macroeconomics*, *76*, 103518.

5. Binswanger, H. P. (1974). A Cost Function Approach to the Measurement of Elasticities of Factor Demand and Elasticities of Substitution. *American Journal of Agricultural Economics*, *56*(2), 377–386.
6. Bui, K. H. N., Jung, J. J., & Camacho, D. (2018). Consensual negotiation-based decision making for connected appliances in smart home management systems. *Sensors*, *18*(7), 2206.
7. Christensen, N. I., & Ramananantoandro, R. (1971). Elastic moduli and anisotropy of dunite to 10 kilobars. *Journal of Geophysical Research*, *76*(17), 4003–4010.
8. Debertin, D. L. (2012). *Agricultural production economics* Library of Congress Cataloging in Publication Data. p 431.
9. Department of Agriculture. (2022). *Baghlan Provincial Agriculture Department*.
10. Du, N., Shao, Q., and Hu, R. (2019). Price Elasticity of Production Factors in Beijing's Picking Gardens. *Sustainability*, *11*(7), 2160.
11. FAO. (2021). *Recent trends and prospects in the global cotton market, along with policy developments*. FAO. https://doi.org/10.4060/cb3269en
12. Feng, Y., Yan, T., Cao, M., & Pan, Y. (2025). Identifying the new momentum from the instrumental substitution of the energy industry in China: Empirical evidence from the ultra-high voltage transmission projects. *Energy*, *320*, 135198.
13. Forgenie, D., Elbaar, E. F., & Khoiriyah, N. (2023). Estimating household price and income elasticities for animal-derived sources of food using the QUAIDS model: the case of Jakarta, Indonesia. *Tropical Agriculture*, *100*(4), 317–328.
14. Griffin, R., Rister, M., & Montgomery, J. (1987). Selecting functional from production analysis. *Western Journal of Agricultural Economics*, *12*, 216–227.
15. Gu, T., Liu, X., Cao, Z., & Lu, W. (2025). Effects of Rising Rural Labor Prices on Land Use Pattern: Evidence from Grain Production in China. Land, 14(1), 112.
16. Hussain, S., Nisar, U., & Akram, W. (2020). An analysis of the cost structure of food industries in Pakistan: An application of the translog cost function. The Lahore Journal of Economics, 25(2), 1–22.
17. Johansen, L. (1972). Production Function: An Integration of Micro and Macro, Short Run and Long Run Aspects. *Amsterdam: North-Holland Publishing Company*.

18. Kandpal, A., Kar, A., Immanuelraj, K., Singh, A., Jha, G. K., & Singh, P. (2022). Insights on ownership patterns and demand for machinery in Indian agriculture. *The Indian Journal of Agricultural Sciences*, *92*(1), 18-21
19. Khan, M. A., Wahid, A., Ahmad, M., Tahir, M. T., Ahmed, M., Ahmad, S., & Hasanuzzaman, M. (2020). World Cotton Production and Consumption: An Overview. In *Cotton Production and Uses* (pp. 1–7). Springer Singapore
20. Knoblach, M., and Stöckl, F. (2020). What Determines the Elasticity of Substitution between Capital and Labor? A Literature Review. *Journal of Economic Surveys*, *34*(4), 847–875.
21. Koç, E., and Karayiğit, B. (2022). Assessment of Biofortification Approaches Used to Improve Micronutrient-Dense Plants That Are a Sustainable Solution to Combat Hidden Hunger. *Journal of Soil Science and Plant Nutrition*, *22*(1), 475–500.
22. Kuroda, Y. (1987). The Production Structure and Demand for Labor in Postwar Japanese Agriculture. *American Journal of Business Management, 4*(6), 1126-1130.
23. Landolsi, M., & Miled, K. B. H. (2024). Semi-Nonparametric Estimation of Energy Demand in Tunisia. *International Journal of Energy Economics and Policy*, *14*(1), 254.
24. Mahmoodi, S. M. (2008). Integrated Water Resources Management for Rural Development and Environmental Protection in Afghanistan. *Journal of Developments in Sustainable Agriculture*, *3*(1), 9–19.
25. Miljkovic, D., Dalbec, N., & Zhang, L. (2016). Estimating dynamics of US demand for primary fossil fuels. *Energy Economics*, *55*, 284–291.
26. Ministry of Agriculture. (2017). *Cotton Sector Market Systems Analysis Report in Balkh and Samangan Provinces, Afghanistan.*
27. Morishima (1967). A Few Suggestions on the Theory of Elasticity. *Keizai Hyoron (Economic Review)*, *16*(1), 144–150.
28. Mufutau Opeyemi, B. (2021). Path to sustainable energy consumption: The possibility of substituting renewable energy for non-renewable energy. *Energy*, *228*, 120519.
29. Ning, F., Shi, Y., Cai, M., Xu, W., and Zhang, X. (2020). Manufacturing cost estimation based on the machining process and a deep-learning method. *Journal of Manufacturing Systems*, *56*, 11-22.

30. O'Brien, R. M. (2007). A Caution Regarding Rules of Thumb for Variance Inflation Factors. *Quality & Quantity, 41*(5), 687–699.
31. Pang, Y., Dang, J., and Xu, W. (2021). Elasticity of Substitution, Price Effect, and Sustainable Fertilizer Use: A Translog and SUR Analysis in China. *Prague Economic Papers*, *30*(2), 189–215.
32. Pippa Rochelle, T. C., & Ferreira Filho, J. B. de S. (1999). The translog cost function and the cotton inputs market in the state of São Paulo: The case from Campinas. Revista de Economia e Sociologia Rural, 37(2), 185–202.
33. *Provinces;Afghanistan*.https://www.ilo.org/wcmsp5/groups/public/ed_emp/documents/publication/wcms_695364.pdf
34. Radmand, H., Keramatzadeh, A., Joolaie, R., and Eshraghi, F. (2021). Economic Investigation of Cotton Production in Afghanistan. *Journal of Iran Cotton Research*, *9*(2), 41–62.
35. Ranjbar, H., Mozafari Shamsi, H., Mohamadi, V., and Mirzaii, F. (2023). Measuring Price and Income Elasticity of Demand Function of the Iranian Imports. *Iranian Economic Review*, *27*(1), 171–185.
36. Ray, S., Haqiqi, I., Hill, A. E., Taylor, J. E., and Hertel, T. W. (2023). Labor markets: A critical link between global-local shocks and their impact on agriculture. *Environmental Research Letters*, *18*(3), 035007.
37. Ren, C., Jin, S., Wu, Y., Zhang, B., Kanter, D., Wu, B., and Gu, B. (2021). Fertilizer overuse in Chinese smallholders due to a lack of fixed inputs. *Journal of Environmental Management*, *293*, 112913.
38. Scheierling, S. M., Loomis, J. B., and Young, R. A. (2006). Irrigation water demand: A meta-analysis of price elasticities. *Water Resources Research*, *42*(1).
39. Shabaneh, M. (2019). *World cotton production by country worldwide 2019.* Statista. Retrieved from https://www.statista.com/aboutus/our-research-commitment/1239/m-shahbandeh
40. Stern, D. I. (1997). Limits to substitution and irreversibility in production and consumption: A neoclassical interpretation of ecological economics. *Ecological Economics*, *21*(3), 197–215.

41. Surya, B., Menne, F., Sabhan, H., Suriani, S., Abubakar, H., and Idris, M. (2021). Economic Growth, Increasing Productivity of SMEs, and Open Innovation. *Journal of Open Innovation: Technology, Market, and Complexity*, *7*(1), 20.
42. Tokel, D., Dogan, I., Hocaoglu-Ozyigit, A., and Ozyigit, I. I. (2022). Cotton Agriculture in Turkey and Worldwide Economic Impacts of Turkish Cotton. *Journal of Natural Fibers*, *19*(15), 10648–10667.
43. Uri, N. D., and Konyar, K. (1990). Energy substitution in cotton production in the USA. *International Journal of Energy Research*, *14*(8), 849–857.
44. Uzawa, H. (1962). Production Functions with Constant Elasticities of Substitution. Review of Economic Studies, 29(4), 291–299.
45. Wang, P., & Wu, G. (2025). Modernization and Elasticity of Substitution in China's Grain Production: Evidence from 1991 to 2023. *Agriculture*, *15*(12), 1247.
46. Wang, P., & Wu, G. (2025). Modernization and Elasticity of Substitution in China's Grain Production: Evidence from 1991 to 2023. *Agriculture*, *15*(12), 1247.
47. Wijetunga, C. S. (2023). Rice production structures in Sri Lanka: the normalized translog profit function approach. *Asian Journal of Agriculture and Rural Development*, *6*(2), 21-35.
48. Wijetunga, C. S., 2016. "Rice Production Structures in Sri Lanka: The Normalized Translog Profit Function Approach," Asian Journal of Agriculture and Rural Development, Asian Economic and Social Society (AESS), vol. 6(02):21-35.
49. Zha, D., and Ding, N. (2014). Elasticities of substitution between energy and non-energy inputs in China's power sector. *Economic Modelling*, *38*, 564–571.
50. Zhang, J., & Zhou, H. (2019). Substitution elasticity of labor and machinery in the production of rice under the background of mechanization: based on the survey data of rice farmers in Jiangsu Province. *Journal of Southern Agriculture*, *50*(2), 432–438.

تخمین کشش‌های قیمتی و جانشینی نهاده‌های تولید پنبه: شواهد تجربی از استان بغلان، افغانستان

حفیظ الله رادمند، علی کرامت زاده، رامتین جولایی، و فرشید اشراقی

چکیده

پنبه به عنوان یک محصول مهم، محصولات متعددی را برای مصارف انسانی تأمین می‌کند و طیف وسیعی از کاربردهای صنعتی را پشتیبانی می‌کند. هدف این مطالعه، تخمین کشش‌های قیمتی و جایگزینی بین نهاده‌های تولید پنبه در استان بغلان افغانستان است. داده‌ها از طریق ۱۳۲ پرسشنامه و با استفاده از نمونه‌گیری تصادفی طبقه‌بندی‌شده از پنبه‌کاران این استان جمع‌آوری شد. روابط بین نهاده‌های تولید با استفاده از تابع هزینه ترانسلوگ در رابطه با رویکرد رگرسیون به ظاهر نامرتبط (SUR) بررسی شد. نتایج نشان داد که کشش‌های قیمتی تقاضا برای زمین، کود حیوانی، کود فسفات، کود اوره، بذر، نیروی کار، آب و ماشین‌آلات به ترتیب ۰.۰۳۶-، ۰.۸۱۵-، ۰.۰۵۶-، ۰.۰۵۰-، ۰.۰۵۶-، ۰.۰۹۲-، ۰.۰۷۴- و ۰.۱۹۸- بودند. همه کشش‌های قیمتی تقاضای نهاده‌ها کمتر از یک بود که نشان‌دهنده تقاضای بی‌کشش است، یعنی استفاده از نهاده‌ها به تغییرات قیمت حساسیت زیادی ندارد. کشش‌های متقاطع تقاضا برای نهاده‌ها نیز کمتر از یک بود که نشان‌دهنده‌ی بی‌کشش بودن تقاضا در بین تمام نهاده‌ها بود. مقادیر کوچک کشش‌های جانشینی نیز نشان داد که سیاست‌هایی که یک نهاده را هدف قرار می‌دهند، تأثیر کمی بر تخصیص سایر نهاده‌ها خواهند داشت. بنابراین، توصیه می‌شود که سیاست‌گذاران از تمرکز بر نهاده‌های منفرد اجتناب کنند و در عوض، هنگام طراحی سیاست‌های کشاورزی، تمام نهاده‌ها را به عنوان یک سیستم یکپارچه در نظر بگیرند.