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ASSESSING THE ECONOMIC EFFICIENCY OF MAIZE FARMERS IN SOUTHERN KHYBER PAKHTUNKHWA, PAKISTAN

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ABSTRACT

This research evaluates economic efficiency of maize growers of in southern Khyber Pakhtunkhwa province, Pakistan. Districts Dera Ismail Khan (DI Khan) and Bannu. A multi-stage random sampling procedure was employed for selection of 100 maize farmers, fifty respondents from district DI Khan and fifty from district Bannu. Cross-sectional primary data was gathered from sampled respondents through a well-structured and pre-tested interview schedule. Cobb-Douglas type stochastic production function and stochastic frontier cost function were estimated by using Maximum Likelihood Estimation (MLE) techniques through Stata 17 software. Production inputs such as land, labor, seed, tractor hours, irrigation numbers, urea, DAP, farmyard manure (FYM), and pesticides were included in the production model. Socio-economic characteristics such as age, farming experience, education, family size, tenure status, off-farm income and farm-to-home distance were considered as explanatory variables in inefficiency effect model. Additionally, production risk variables i.e., average maximum temperature, average minimum temperature, and average rainfall were included to evaluate their impact on technical efficiency of farmers. Results showed that the average yield and net return per acre were 824 kg and Rs. 26,898, respectively in district DI Khan whereas 736 kg and Rs. 22,166 per acre were recorded in district Bannu. The coefficients of the estimated production function indicated that seed rate, labor days, urea, DAP, farmyard manure (FYM), and pesticides have statistically significant effect on maize production. In contrast, the effects of cultivated area, tractor hours, and number of irrigations were statistically insignificant. This can be attributed to the lack of substantial variation in these particular inputs among the sampled farmers, due to hilly area cultivation of maize were carried on terracing with minimum utilization of tractor/farm machinery. The mean technical efficiency was estimated to be 0.81. This suggests maize farmers could improve yields by up to 19% using existing input levels. Among the climatic risk factors, average maximum temperature showed a significant negative relationship with technical inefficiency, suggesting improved efficiency with higher temperatures up to a point. Average minimum temperature had a positive and significant relationship with inefficiency, while rainfall showed a negative but statistically insignificant effect. Mean allocative efficiency was estimated for District DI khan was 0.57, indicating that production costs could be reduced by 10% per acre. Similarly, the average allocative for District Bannu was estimated 0.60, indicating that production cost could be reduced by 24%. Economic efficiency was relatively low (0.32 average), with no farmer achieving full efficiency. To enhance economic efficiency, key focus areas including strengthening formal and informal education, promoting coordination and cooperation

among stakeholders (farmers, agricultural research and extension services, and input dealers), and implementing fair and consistent output pricing policies. Due to variation in terms of relationship within efficiency and farmers socioeconomic factors among districts, need based policies are essential to guide farmers for advancement in maize production.

Key words: *Maize production, technical efficiency, Allocative efficiency, Economic efficiency, Khyber Pakhtunkhwa, Pakistan.*

INTRODUCTION

Agriculture remains the cornerstone of Pakistan's economy, driving food security, employment, poverty reduction, and foreign exchange earnings. Contributing 24% to GDP and employing 37.4% of the labor force, around 65–70% of the population depends on agriculture for their livelihood. The sector's growth not only enhances farmers' income and exports but also stabilizes consumer prices, especially critical in the post-COVID-19 era of global food inflation. In 2023–24, Pakistan's agriculture sector grew by 6.25%, led by an 11.03% rise in the crop sub-sector. Major crops such as cotton (up 108.2%), rice (34.8%), and wheat (11.6%) fueled this performance, supported by favorable prices, government policies, quality inputs, and timely credit. However, declines were seen in sugarcane and maize due to changing cropping patterns. Recognizing agriculture's vital role, policymakers increasingly focus on enhancing efficiency rather than solely expanding inputs, particularly through better technology use among small-scale farmers. This shift is crucial for improving productivity and rural livelihoods. Among staple cereals, maize globally third in cultivation after wheat and rice holds great potential. In Pakistan, maize production is expanding, yet yield disparities, particularly in provinces like Khyber Pakhtunkhwa, highlight the need for greater economic and allocative efficiency to bridge productivity gaps and ensure food security. (GoP, 2024)

In Pakistan, maize ranks as the third most significant cereal crop after wheat and rice. Its adaptability to diverse climatic zones makes it a viable option across the country. However, despite its potential, Pakistan's average maize yield (5,999.2 kg/ha) is significantly lower than that of leading producers like the USA, Canada, and Uzbekistan, ranking the country 54th globally. This low productivity raises concerns about how to enhance maize output. [Food and Agriculture Organization (FAOSTAT 2023)].

Research highlights three strategies to improve agricultural productivity: adopting modern technologies, reducing input costs, and enhancing farm management practices. However, the high cost of inputs, limited R&D investment, and slow development of improved crop varieties pose challenges. With the COVID-19 pandemic worsening economic conditions and increasing input costs, effective management practices become the most practical and immediate option.

Economic efficiency comprised of technical efficiency (TE) and allocative efficiency (AE) is key to addressing these issues. TE refers to maximizing output with given inputs, while AE ensures resources are used in a cost-effective manner. Combined, they form economic efficiency, a vital measure for sustainable agriculture.

Maize has long served as both a food and industrial crop in Pakistan. Historically consumed as a staple in rural households, its usage has shifted: now about 60% of production is used in poultry feed, 30% in wet milling, and the rest for food and seed. Despite its high nutritional and industrial value, the yield gap remains significant potential yield is estimated at 7,184 kg/ha, while the actual average is just 4,425 kg/ha. (GoP 2020)

Khyber Pakhtunkhwa (KP) is a key maize-producing province, with Swat, Mardan, Mansehra, Buner, DI Khan and Bannu being major contributors. Yet, yields remain lower than their potential due to inefficiencies in input use and lack of modern practices.

This study focuses on evaluating the economic efficiency of maize production in districts DI Khan and Bannu situated in southern Agro-ecological Zone of Khyber Pakhtunkhwa province. It aims to calculate the cost of production, estimate technical and allocative efficiencies, and identify the factors contributing to inefficiencies. The findings will offer valuable insights to farmers, policymakers, and

agricultural stakeholders, ultimately helping to improve maize productivity and profitability in the region.

1. Approach and Methods: Data Gathering and Modeling

A well-structured interview schedule was developed and pre-tested in line with the study's objectives. Primary data were collected directly from 50 maize growers in DI Khan district, 29 from the village Yarik and 21 from Chehkan and 50 growers in Bannu district, including 23 respondents from Tlagi, Jani khel and 22 from Khwagamad.

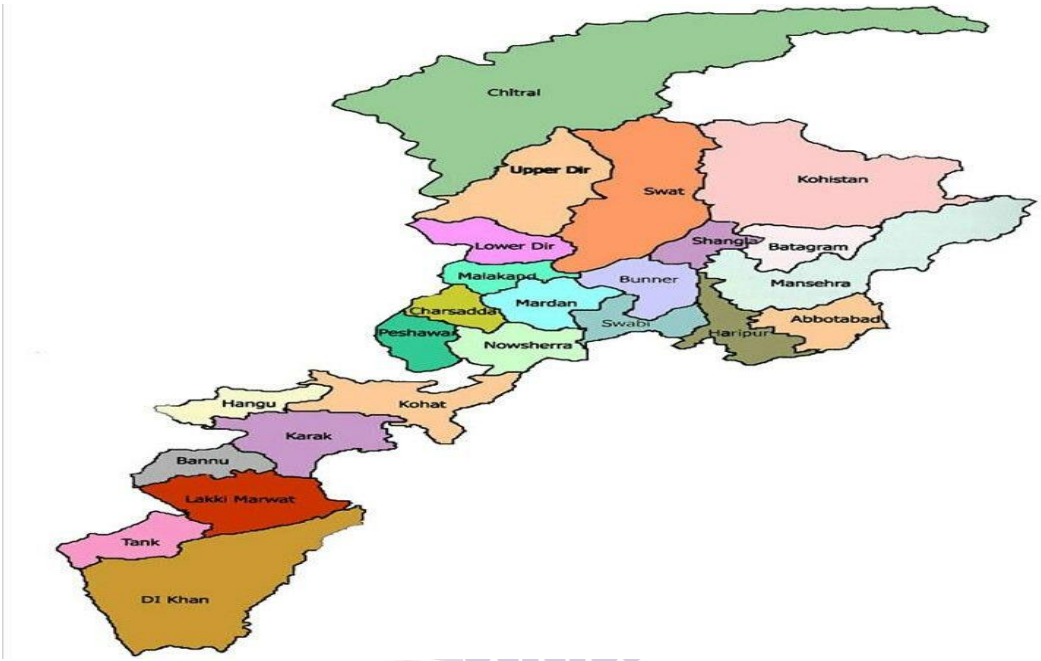


Figure 1 Map of Khyber Pakhtunkhwa province

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2.1 Data collection procedure

The research study incorporated both primary and secondary data. Primary data was obtained through a cross-sectional survey, typically conducted using a structured interview schedule to gather information from a sampled respondent. Secondary data, on the other hand, was collected from various published and unpublished sources, such as existing research studies, reports, databases, and other relevant documents. Survey research technique not only provide strategic composition of data gathering but also provide scientific management ideas for the study. Such type of research technique is useful method to obtain significant detail through well-defined structured interview schedule from concerned respondents. This research methodology is implementing by researchers to investigate a diverse array of challenges encountered in the field (Gaillet *et al.* 1996).

2.2 Analytical framework

The efficiency analysis, which originated from Farrell (1957), serves as the foundation for various research methodologies aimed at evaluating efficiency and productivity. The Average Production Function and Frontier Approach are the two main methods for calculating efficiency that are highlighted in the literature. Aigner, Lovell, and Schimidt (1977) have pointed out that the Average Production Function technique provides average production but doesn't reveal the highest achievable production. As a result of this drawback, frontier approach was developed. In current research investigation this technique is widely implementing in different efficiency measurement. Frontier Approach can be broadly classified in two categories: parametric and non-parametric methods, which is elaborated in the subsequent sections;

2.3 Per acre cost, gross revenue and net revenue of maize crop

The costs accrued by maize farmers throughout the entire crop season are referred to as the cost of production. This includes expenses of various factors of production i.e., seed, machinery/tractor hours, irrigation, chemical fertilizers (urea, DAP), organic fertilizer (farmyard manure), , insecticides, weedicides, labor days, and land rent, calculated on the basis of prevailing market prices.

The formula presented by Debertin in 2003, as shown in equation (1), was applied to calculate the total cost, gross revenue, and net return. This formula has been widely employed in previous research studies by scholars such as Ahmad *et al.* (1994, 2003, 2004, 2019), Hussain *et al.* (2004), Ali (2012), Aftab *et al.* (2019), Ali *et al.* (2019), Murtaza *et al.* (2020), and Khan *et al.* (2020).

$$NR_i = GR_i - TC_i \quad (1)$$

$$GRi = P_i \times Y$$

$$TCi = P_{xi} \times X_i$$

Whereas;

P_i = Current market price for per unit of output

Y_i = Yield (Kg/Hectare)

X_i = Quantity of inputs utilized by the i^{th} farmer

P_{xi} = Inputs prices

Here, $\mathbf{NR_i}$ represent the net revenue per hectare, while $\mathbf{GR_i}$ refers to the gross revenue per hectare for the i^{th} farm. Gross revenue is calculated by multiplying the yield per hectare by the unit price of the output. $\mathbf{TC_i}$ represents the total cost of variable inputs, which includes expenditures incurred on the purchase of inputs.

2.4 Non-parametric Methods

The non-parametric approach to efficiency measurement encompasses modeling techniques that utilize envelopment methods and linear programming for estimation. This method does not impose specific functional forms or make distribution assumptions about the error term. A well-known technique falling under this category is Data Envelopment Analysis (DEA), which was originally introduced by Farrell (1957) and later refined by Charnes *et al.* (1978) as an estimation tool. DEA methods are designed to assess production and cost efficiency without parameterizing underlying model. These methods started with hypothesis of existence of a production frontier, which work as a boundary or limit within which producers in an industry should operate efficiently. Furthermore, inherent variations amongst producers result in them operating at varying ranges from this effective production frontier/boundary.

To assess efficiency, DEA constructs a structure or envelope around the observed data, allowing researchers to identify which producers are closer to the frontier (i.e., more efficient) and which are farther away (i.e., less efficient). DEA primarily relies on making relative comparisons among observed producers and does not involve traditional statistical hypothesis techniques. The non-parametric approach to efficiency measurement can be classified into two main categories: Frontier methods and Non-Frontier methods. Frontier methods include techniques like data envelopment analysis, whereas non-frontier methods rely on index numbers, as explained by Vasilis (2002).

2.5 Parametric approach

The parametric technique to efficiency measurement offers certain advantages over the non-parametric approach because it involves not only specifying the functional form of production approach but also establishing supposition regarding distribution of error terms, as emphasized by Aye (2010). This concept can be further categorized into frontier and non-frontier models. The frontier technique consists of both deterministic and stochastic frontier models, while the non-frontier method involves simpler regression analysis. Practical applications tend to favor the use of the stochastic frontier analysis method, as suggested by Kumbhakar and Bhattacharyya (1992) and Vasilis (2002).

In the following two subsections, we will provide an illustration of parametric frontier stochastic models, which include both deterministic and stochastic frontiers. For clarity in presentation, the dependent variable Yi has been expressed in relation to an input Xi, incorporating stochastic errors and unobservable random variables.

2.6 Deterministic frontier function

A deterministic frontier model is characterized by estimating outputs based on established relationship between inputs and outputs, without allowing for random variations. This function

supposes that any deviation from the frontier is solely attributed to inefficiency, as described by Battese in 1992.

Y_i = f (A_k, B) expected (- μ_k) k = 1,2,3.....N (2)

Whereas:

Y_i = Represent possible output of i^{th} sample farmer

f(A_k, B) = Represent appropriate function of inputs A_K for the k^{th} firm and unknown parameters (B_i)

μ_k = Represent error term

Variable μ_i define kind of technical inefficiency ranges from zero to one. The model (2) is referred to as deterministic because the output is restricted over by the deterministic quantity i.e. f(A_k, B). In deterministic frontier model in equation (2), TE and frontier production of ki^{th} firm are depicted below:

Y_k = f(A_K, B) (3)

TE_i = $\frac{Yk}{Yk*}$ (4)

= $\frac{f(Ak,\ B)\exp(-\mu k)}{f(Ak,\ B)}$

= exp (-μ_k)

In the deterministic frontier production equation (2), individual firm's technical efficiency can be ascertained by calculating the ratio of its actual output to the output achieved at the corresponding frontier.

The formula for determining technical efficiency (TE^) in the deterministic frontier production function equation (2) is expressed as TE^ = Y_k / f(A_k, B^), where B^ is calculated by using either Maximum Likelihood Estimation (MLE) model or Corrected Ordinary Least Squares (COLS) model. When it comes to the MLE technique, it's important to note that conclusion about the factors (β) can't be achieved, when μ_k, representing the deterministic frontier's error term, follows an exponential or half-normal distribution, as these distributions do not satisfy the necessary regularity condition.

According to Green's (1980), this regularity condition is met when μ_k follows an independent and similar distribution, such as gamma random variables with determinates r > 2 and λ > 0. Green referred to that as a sufficient condition under which maximum likelihood estimators exhibit the normal asymptotic properties, thereby allowing for interpretation about B determinates to be achieved through MLE methods.

2.7 Stochastic frontier function (SFF)

The term "Stochastic" refers to a scenario or function that incorporates element of randomness, enabling it to address issues related to measurement of errors and various other unpredictable influences that can contribute to inefficiencies on the part of producers, as explained by Green (2008). Battese, (1992), elaborated that the stochastic frontier function not only takes into account the production function but also factors in certain random external variables. The development of the stochastic frontier model was motivated by the recognition that the diversion from the frontier/boundary may be not under the entire command of the producers. The stochastic frontier function has been formally stated through equation (4).

Y_j = f (A_j, B) exp (v_j+μ_j) j = 1,2,3.....N (5)

In this context, v_j represents the two-sided error terms, encompassing the determinates beyond from producer command of control. These error terms are supposed to follow an independent and normal distribution with a mean of zero and variance of σ^2 v, specifically N (0, σ^2 v). In this function, where potential output is constrained from beyond the stochastic amount f (A_j, B) exp (v_j), is mention as the stochastic frontier model.

Conversely, the word μ_j refers to the one-sided efficiency component, which is employed in the analysis of the production inefficiency impact. μ_j can be described as following an exponential, gamma, or half-normal distribution, as discussed in the works of Aignar *et al.* (1977), Greens (1980).

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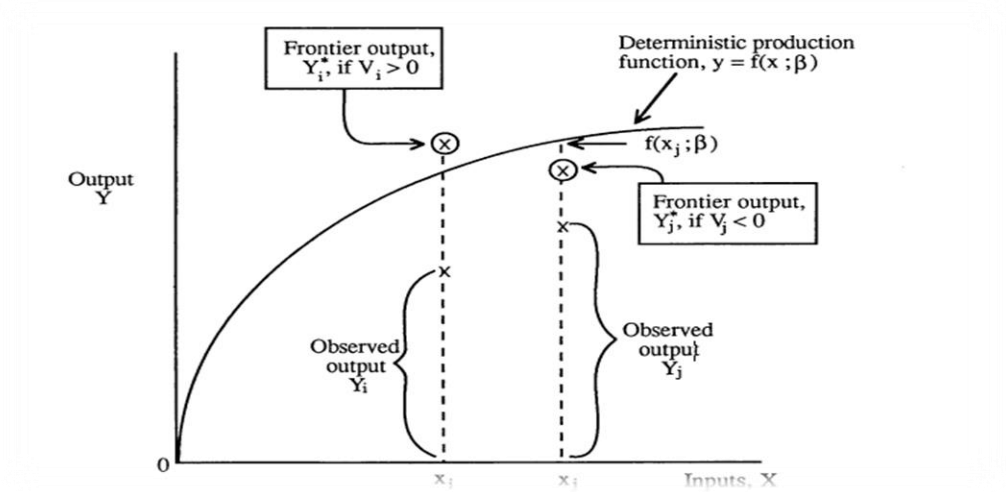


Figure 1 Stochastic frontier production function

Figure 1 provides an illustrative representation of the core graphical design of the stochastic frontier function, as illustrate in equation (5). This representation pertains to the evaluation of production functions for two producer firms, denoted as i^{th} and j^{th}. In the case of firm i^{th}, its production (Yi) achieved through the input vector Xi surpasses the frontier output Yi*, which is determined by the deterministic production function f(Xi, β). This favorable outcome for firm i^{th} is attributed to its operation under conducive conditions, resulting in a positive Vi. Conversely, firm j^{th} generates output Yj employing input vectors Xj, but it falls short compared to the deterministic production function f(Xj, β) due to adverse productivity situation. This discrepancy results in a negative random error, Vj. In both instances, the observed production remains below the frontier production. However, it is expected that the unobservable production frontier for the studied firms closely aligns with the deterministic production function.

In accordance with the suppositions of stochastic frontier function (SFF), Maximum Likelihood Estimation (MLE) techniques provide conclusions about the model's parameters under the condition that standard regularity conditions are met. Various researchers, including Aigner, Lovell, and Schmidt (1977), have mentioned that Maximum Likelihood estimation of the factors can be estimated by using the parameterization techniques (β = β* + δ and σ^2 = σ^2*).

Regarding the concept of technical efficiency for an individual firm, it remains consistent between both the deterministic (2) and stochastic (4) models. It is defined as the ratio of actual (observed) output to the corresponding frontier output, as shown below:

Technical Efficiency (i) = Yí / Y*í (6)

Technical Efficiency (i) = f(Xi, β) exp (- μi) /f (Xi,β) (7)

Equations (2) & (5) provide identical TE values for a firm in both the deterministic and stochastic models. However, as illustrated in Figure (1), these equations produce different outcomes for two functions. More precisely, the TE of firm "a" within the stochastic frontier model (SFM) surpasses that within the deterministic frontier model (DFM). i.e., Yí / Y*í > (Yí / f (Xí, β)

Firm "j^{th}" experiences less adverse conditions (i.e., Vj < 0) within the stochastic frontier compared to the deterministic function f(Xj, β), while firm i^{th} demonstrates lower TE due to the presence of favorable conditions (i.e., Vj > 0) within the deterministic function. In practical terms, when analyzing a specific dataset, the computed TE obtained from SFM often appears higher than those derived from a DFM. This is because the SFM accounts for determinants that allow output values to surpass the deterministic frontiers.

2.8 Stochastic frontier approach (SFA)

The initial implementation of stochastic frontier production method to agrarian data was introduced by Battese and Cora (1977). This pioneering work laid the foundation for the assessment of individual grower performance

levels. The method is formally illustrated in the given below equation 3.8.

$Y_i = f(A_i, \beta)$ ($_i$ = 1,2...n) (8)

$Y_i = \beta_o + \beta_i A_i + \varepsilon_i$ (9)

Where;

Y_i = Production of $_i^{th}$ grower

β_o = Intercept/constant

β_i = Coefficient to be estimated

A_i = Total inputs utilized in the whole crop period by $_i^{th}$ grower.

ε_i = Error term of $_i^{th}$ grower, which is calculated by subtracting estimated output from observed output

$\varepsilon_i = v_i - \mu_i$

v_i = Error term to natural factor, beyond the control of farmers (N~ (0, σ^2)

μ_i = Error term associated with t^{th} grower.

In the error term, one element, V_i ($-\infty < V_i < \infty$), is supposed to be evenly, independently, and normally distributed with a mean of 0 and constant variance denoted as σ^2. Conversely, μi can adhere to a range of distributions, including gamma, exponential, truncated normal and half-normal distributions, as discussed in the works of Aigner *et al.* (1977) and Steveinson (1980). However, in the current research study, μi follows a half-normal distribution that is slight below at zero, represented as μi ~ N(0, σ_ μ^2), which is a commonly employed approach in the literature related to applied stochastic frontier analysis. It's worth emphasizing that in the composed error term, if the component ν is equal to 0, the model simplifies to the deterministic frontier. Conversely, when μ is equal to 0, the model shifts to the stochastic frontier model. This distinction highlights the flexibility and versatility of the model in accommodating both deterministic and stochastic components in the analysis of production efficiency (Zelliner, Kmeenta and Draeze, 1966).

The error terms, denoted as v and μ, are assumed to be independent from each other.

2.9 Techniques to estimate stochastic frontier production function

Estimating production functions along with examining the "Duality theory", which establishes a connection between production and cost functions, is considered a suitable and preferred area in applied econometrics. Generally, Least Squares or Correlated Ordinary Least Squares (COLS) methods are employed, assuming normally distributed disturbances to analyze the model. It has been debated that the selected approach and the specific error term of distribution must be aligned with characteristics of the data. Frontier Production Approach can be calculated by employing either the COLS or Maximum Likelihood Estimation (MLE) approaches. In cases where there is an asymmetric distribution of disturbances, using the MLE technique has been shown to yield significantly higher efficiency estimates compared to COLS. Furthermore, when dealing with asymmetric error term distributions, MLE provides efficient and asymptotically reliable results, as outlined by Green in 1980. Given the assumptions about the error term distribution as presented in Eq (6), the Maximum Likelihood Technique (MLE) will be utilized in the current research study.

Jondrow *et al.* (1982) highlighted the assumptions concerning the statistical distribution of v and μ, as discussed earlier, enable the computation of conditional mean of μi of error εi.

$$E(\mu_i | \epsilon_i) = \sigma^* \left[\frac{f^*(\epsilon i,\ \lambda/\sigma)}{1 - F^*(\epsilon i,\ \lambda/\sigma)} - \frac{\epsilon i, \lambda}{\sigma} \right] \quad (10)$$

Here, F* and f* are symbols of standard normal density and distribution functions, respectively, estimated at εi, λ/σ, and σ^2 = σ^2v + σ^2μ. σ^2v and σ^2μ are the variances of vi and μi. The symbol λ denotes the proportion of standard errors (λ = σμ/σv). The Eq (8) provides computation of μ and v after substituting ε, λ, and σ from its respective estimates. By subtracting v from both sides of Eq (5), we arrive at the stochastic production frontier.

$Y^* = f(Xi, \beta) - \mu = Y - v$ (11)

Whereas Y* represents the growers obtained yield modified for the statistical noise present in "v", as described by Bravo-Uraeta and Riegier (1991). Aforementioned Eq is subsequently employed to determine the cost frontier.

After a series of successive modifications and suggestions from various researchers, including Battrese *et al.* in 1988 and 1992, the maximum likelihood approach of the model is defined in Eq (3.8) can be formulated as follows:

$\ln(L) = -\frac{N}{2}(\ln(\frac{\pi}{2}) + \ln\sigma 2) + \sum_{j=1}^{N} \ln[1 - \phi(\frac{\varepsilon j\sqrt{\gamma}}{\sigma\sqrt{1-\gamma}})] - \frac{1}{2\sigma 2}\sum_{j=1}^{N} \varepsilon 2$ (12)

Where;

$\varepsilon_i = Y_i - X_i\beta$, $\sigma 2\varepsilon = \sigma 2v + \sigma 2\mu$, ($\sigma 2v$ and $\sigma 2\mu$ described variance of v and μ respectively), F defined cumulative density function (cdf), that is calculated at ($\lambda\epsilon / \sigma$). For MLE analysis first order partial derivatives about β, λ and $\sigma 2\varepsilon$ are set equal to zero and solve at the same time.

2.10 Allocative efficiency of producer

The sole farmer's allocative efficiency can be described as the ratio of minimal cost to the actual cost, as expressed in equation (13)

$AE_i = Exp_i^* / Exp_i$ (13)

Whereas:

AE_i = Represent allocative efficiency of i^{th} farm

Exp_i^* = Represent minimal feasible i^{th} farm cost

Exp_i = Represent actual i^{th} farm cost

Allocative efficiency (AE) limit from zero (0) to one (1)

The single farmer allocative inefficiency was calculated via formula provided in equation (14)

Allocative inefficiency (AI) = 1- AE (14)

AI = $1 - [\text{mnimim expendure } (Expi^*)] / [\text{observed Expenditure } (Expi)]$

2.11 Allocative inefficiency model estimation

In the estimation of allocative inefficiency, it is mandatory to assume a normal distribution for $V_i\{Vi \sim N(O, \sigma_v^2)\}$ and a half normal distribution for μi $\{\mu i \sim N(O,\sigma_u^2)\}$. Factors of allocative inefficiency are given in equation (15).

$-\mu i = \varphi_0 + \varphi_i Zi + \epsilon i$

$\mu_i = \varphi_0 + \varphi_1 Z_{1i} + \varphi_2 Z_{2i} + \varphi_3 Z_{3i} + \varphi_4 Z_{4i} + \varphi_5 Z_{5i} + \varphi_6 Z_{6i} + \varphi_7 Z_{7i} + \omega_i$ (15)

Whereas:

μ_i = Represent dependent variable of allocative inefficiency

Z_{1i} = Represent i^{th} farmer Age (Years)

Z_{2i} = Represent i^{th} farmer number of schooling in years

Z_{3i} = Represent i^{th} farmer number of experience in years

Z_{4i} = Dummy for tenurial status (1 for owner, 0 for tenants and 2 for Owner-cum tenants)

Z_{5i} = Represent i^{th} farmer distance between farm and house in kilometer

Z_{6i} = Dummy for off farm income (1 if farmer has off-farm activities otherwise 0)

Z_{7i} = Represent family size of farmer in number

ω_i = Random error term (normally distributed with 0 mean and constant variance)

In the context of the allocative inefficiency model, φ_0 represent a constant, while φ_i are the parameters that need to be calculated.

2.13 Economic efficiency

The Farrell's (1957) defined that economic efficiency encompasses both technical efficiency and allocative efficiency. It can be seen as the proportion between the lowest observed production expenditure and the actual expenditure of production. Economic efficiency is usually represented as a value between zero and one (0 to1) and calculated by multiplying the estimated technical efficiency and allocative efficiency, show in the Eq (16).

EE = TE*AE (16)

In equation 16, EE stands for economic efficiency, TE represents technical efficiency, and AE denotes allocative efficiency.

3. Result & Discussion

3.1 Descriptive statistics of key explanatory variables

Descriptive statistics are indeed valuable for summarizing and simplifying data, making it easier to understand the features of maize sampled respondents. These statistics are essential for understanding the range, central tendency, and variability of the important independent variables that are added in stochastic frontier model on a per acre basis. This summary provides a foundational understanding of the data distribution, which is crucial for further analysis in your study. Table 1 presents the descriptive statistics for the sampled maize growers, encompassing the

mean, standard deviation, minimum, and maximum values.

As presented in Table 1, the average maize yield per acre in the DI Khan district was measured at 824 kg, with yields varying from a low of 635 kg to a high of 920 kg. The standard deviation of 91.38 kg indicates significant variability in maize yields among the respondents surveyed. The average area dedicated to maize cultivation was 4.74 acres, with a standard deviation of 2.77, ranging from 1 acre to 10 acres. Labor input averaged 10.84 man-days per acre, with a minimum of 9 and a maximum of 16 man-days, resulting in a standard deviation of 2.21. The average seed rate for maize was found to be 10.46 kg $acre^{-1}$, with a standard deviation of 3.26 kg, and a range from 7 kg to 17 kg. The mean tractor hours utilized were 1.61, with a minimum of 1 hour and a maximum of 3 hours, showing a standard deviation of 0.52, which reflects minimal variability in tractor usage across the research area. On average, there were 5.70 irrigation applications, with a standard deviation of 0.79, ranging from 5 to 7 applications per acre. The average application rates for Urea and DAP per acre were 79.50 kg and 43.64 kg, respectively, with standard deviations of 25.10 kg and 10.03 kg. The application of Urea and DAP varied from a minimum of 25 kg and 28 kg to a maximum of 100 kg and 63 kg, respectively. There was notable variability in the application of farmyard manure (FYM) and pesticides among the surveyed maize growers. Additionally, the average quantities of FYM and pesticides applied were 320 kg and 3200 milliliters (ml) per acre, with standard deviations of 147.08 kg and 857.14 ml, respectively. The application quantities of FYM and pesticides ranged from a minimum of 100 kg and 2500 ml to a maximum of 600 kg and 4500 ml per acre, respectively.

In the district of Bannu, the mean production per acre of maize was recorded 736.20 kg, with yield ranging from a minimum of 640 kg to a maximum of 820 kg. The substantial standard deviation of 55.69 kg indicated variability in maize yields among the surveyed respondents. The average area allocated for maize cultivation was 2.73 acres, exhibiting a standard deviation of 1.87, with a range from 1 acre to 7 acres. Labor input averaged 11.10 man-days per acre, with a minimum of 9 and a maximum of 15 man-days, resulting in a standard deviation of 1.93. The average seed rate for maize was determined 11.04 kg per acre, accompanied by a standard deviation of 3.56 kg, and a range from 7 kg to 17 kg. The mean tractor hours utilized were 1.62, with a minimum of 1 hour and a maximum of 3 hours. The average tractor hours per acre, showing a standard deviation of 0.56, indicate limited variability in tractor usage throughout the study area. On average, 5.44 irrigation applications were made, with a standard deviation of 0.99, ranging from a minimum of 4 to a maximum of 7 applications per acre. The average application rates of Urea and DAP per acre were 79 kg and 38.7 kg, respectively, with standard deviations of 24.93 kg and 8.77 kg. The application of Urea and DAP varied from a minimum of 25 kg and 27 kg to a maximum of 100 kg and 55 kg, respectively. There was considerable variability in the application of farmyard manure (FYM) and pesticides among the maize growers surveyed. Furthermore, the average quantities of FYM and pesticides applied were 289 kg and 3140 milliliters (ml) per acre, with standard deviations of 158.85 kg and 776.18 ml, respectively. The application quantities of FYM and pesticides ranged from a minimum of 100 kg and 2500 ml to a maximum of 600 kg and 5000 ml per acre, respectively.

Table 1Descriptive statistics of key explanatory variables

District	Variables	Unit	Mean	Std. Dev	Min	Max
DI Khan	Yield	Kg.	824.00	91.38	635	920
	Area	Acre	4.74	2.77	1	10
	Labor days	No.	10.84	2.21	9	16
	Seed	Kg.	10.46	3.26	7	17

	Tractor	Hour	1.61	0.52	1	3
	Irrigation	No.	5.70	0.79	5	7
	Urea	Kg.	79.50	25.10	25	100
	DAP	Kg.	43.64	10.03	28	63
	FYM	Kg.	320.00	147.08	100	600
	Pesticides	ML	3200.00	857.14	2500	4500
Bannu	Yield	Kg.	736.20	55.69	640	820
	Area	Acre	2.73	1.87	1	7
	Labor days	No.	11.10	1.93	9	15
	Seed	Kg.	11.04	3.56	7	17
	Tractor	Hour	1.62	0.56	1	3
	Irrigation	No.	5.44	0.99	4	7
	Urea	Kg.	79.00	24.93	25	100
	DAP	Kg.	38.70	8.77	27	55
	FYM	Kg.	289.00	158.85	100	600
	Pesticides	ML	3140.00	776.18	2500	5000

Source: Field Survey, 2022-23
Where: DAP, FYM, ML, No, Kg stand for Diammonium phosphate, Farmyard manure, milliliter, Number, Kilogram

3.2 Per acre net revenue of maize production

The findings in Table 2 reveal that the gross revenue which includes income derived from both the yield and by-products of maize cultivation in the study area. This figure was determined by multiplying the fresh yield per acre of maize and the by-products by the prevailing prices established by the government of Khyber Pakhtunkhwa. The data in Table 2 further illustrates that the average yield and net return per acre were notably higher in the district DI Khan (824 kg, Rs. 26,898),and District Bannu (736 kg, Rs. 22,166). The finding are consistent with the results of Mannan (2001).

Table 2 Table 2 Per acre gross revenue and net return of maize production

District	Item	Unit	Quantity	Price/Unit	Value (Rs.)
DI Khan	**Yield/Acre**	**Kg.**	824	103	84938
	By Product				23754
	G.R				108692
	T.C/Acre				81794
	N.R				26898
Bannu	**Yield/Acre**	**Kg.**	736	104	76241
	By Product				23352
	G.R				99593
	T.C/Acre				77427
	N.R				22166

Source: Field Survey, 2022-23.
Where G.R= Gross revenue, T.C = Total cost and N.R = Net revenue.

3.3 Maximum likelihood estimates of the Stochastic Frontier Cobb-Douglas Type Production Function

3.3.1 Technical efficiency effect model

Using the software package STATA, Maximum Likelihood Estimates (MLE) were obtained for the Cobb-Douglas production function, with results presented in Table 3. This table displays the coefficients of various input variables, along with their standard deviations and T-ratios in the fourth, fifth, and sixth columns, respectively. The p-values associated with the MLE results are shown in the seventh column. These parameters, representing the elasticities of inputs within the

production process, highlight the significant roles of variables such as seed usage, labor days, urea, DAP, farmyard manure (FYM), and pesticide application in maize production. The estimated elasticities suggest that a 1% increase in seed, labour day, urea, DAP, FYM and pesticides would enhance maize production by 0.14, 0.06, 0.03, 0.16, 0.02 and 0.12 percent respectively. DAP, seed and pesticides contributed the most to maize production, with elasticities of 0.16, 0.14, and 0.12, respectively. All the inputs exhibit both positive and varying degrees of significant and non-significant relationships with maize production. While coefficients for land, tractor hours and irrigation frequency were positive and insignificant at the 5% level. In a Stochastic Frontier Analysis (SFA) model, the lambda (λ) parameter represents the ratio of the standard deviation of the inefficiency term (σ_u) to the standard deviation of random error term (σ_v). In Table 3, the estimated lambda value of 1.34 suggests that the variation in technical inefficiency (σ_u) is 1.34 times that of random noise or external factors (σ_v). The gamma (γ) parameter was used to assess the overall impact of inefficiency on output, as noted by Stefan et al. (2011). Gamma serves as determinant of inefficiency presence within the survey data. According to Table 3, the estimated log-likelihood ratio statistic for model fitness was significant at the 0.05 level, indicating that an OLS estimation would not be suitable for this data. In this study, the gamma value of 0.64 implies that 64% of the variation in maize production can be attributed to technical inefficiency, while the remaining 36% is likely due to random noise.

Table 3 Maximum likelihood estimates of the Stochastic Frontier Cobb-Douglas Type Production Function

Variables	Unit	Parameter	Coefficient	Std. Dev	t-ratios	P-Value
Constant	~	β_0	4.320	0.190	22.68	0.000
Ln Seed	Kg.	β_1	0.145	0.009	14.65**	0.000
Ln Area	Acre	β_2	0.005	0.006	0.88ns	0.381
Ln Tractor	Hour	β_3	0.000	0.000	0.04ns	0.971
Ln Labor	No.	β_4	0.066	0.016	4.03**	0.000
Ln Urea	Kg.	β_5	0.030	0.011	2.71**	0.007
Ln DAP	Kg.	β_6	0.165	0.020	7.96**	0.000
Ln FYM	Kg.	β_7	0.026	0.008	3.14**	0.002
Ln Pesticides	ML	β_8	0.126	0.019	6.37**	0.000
Ln Irrigation	No.	β_9	0.015	0.024	0.63ns	0.530
Dummy 1 (D_1) Zone B		Υ_1	0.446	0.025	17.79**	0.000
Dummy 2 (D_2) Zone C		Υ_2	0.178	0.014	11.04**	0.000
Dummy 3 (D_3) Zone D		Υ_2	0.176	0.015	11.20**	0.000

Source: Study results. Significance level (0.01= **, 0.05 = *, ns = Non significant)

Technical inefficiency effect model

Constant	~	δ_0	8.235	3.888	2.12	0.034
Age	Year	δ_1	0.016	0.119	0.14ns	0.891
Off-farm income	D	δ_2	- 0.691	0.384	- 1.80ns	0.072
Tenurial status	D	δ_3	0.412	0.379	1.09ns	0.277
F.H.D	Km	δ_4	- 0.412	0.243	- 1.69ns	0.090
Education	Year	δ_6	- 1.053	0.212	- 4.95**	0.000
Experience	Year	δ_7	- 0.754	0.186	- 4.04**	0.000
Family size	No.	δ_8	0.046	0.055	0.84ns	0.401
Avg Max Temp	C^0	δ_9	- 0.751	0.211	- 3.56**	0.000
Avg Min Temp	C^0	δ_{10}	0.560	0.154	3.63**	0.000

Rainfall		δ_{11}	- 0.000	0.001	-0.26^{ns}	0.792

Source: Study results. Significance level (0.01= **, 0.05 = *, ns =Non significant)

3.4 Districts frequency distribution of allocative efficiency estimates and summary statistics of maize growers

Table 4 present the frequency distribution of allocative efficiency scores among the sampled farmers, based on the computations derived from Equation 3.20. The average allocative efficiency score for maize growers in District D.I. Khan is 0.57, with scores ranging from a minimum of 0.50 to a maximum of 0.75. This suggests that in order to reach the highest allocative efficiency level of the most efficient growers in the D.I. Khan district, the average grower might cut costs by 24%, or Rs. 19,631 per acre (24% of the total cost of Rs. 81,794). Of the growers, 47 (94%) operate in the 0.50–0.70 range, and 2 (4%) operate in the 0.70–0.80 range. In district D.I. Khan., no farmer was found to have allocative efficiency above 80%, indicating allocative inefficiency.The estimated mean allocative efficiency score in the Bannu district ranges from a minimum of 0.52 to a maximum of 0.67, with an average score of 0.60. As indicated in Table 4.31, all the respondents (100%) operate within the efficiency range of 0.50 to 0.70. The findings suggest that average growers of maize have the potential to reduce their costs by up to Rs. 8,083 per acre, which constitutes 10% of the total cost of Rs. 77,427, in order to reach the maximum allocative efficiency level achieved by the most efficient growers in the district. Notably, no farmer in district Bannu was found to have an allocative efficiency level exceeding 70%, highlighting a significant issue of allocative inefficiency.

Table 4. Districts frequency distribution of allocative efficiency estimates

Efficiency level		<0.50	0.50-0.70	0.70-0.80	0.80-0.90	>0.90	Mean	Min	Max
D DI Khan	No.	1	47	2	0	0	0.57	0.5	0.75
	%	2	94	4	0	0			
Bannu	No.	0	50	0	0	0	0.60	0.52	0.67
	%	0	100	0	0	0			

Source: Author field data estimation through STATA

4.CONCLUSION, LIMITATION AND RECOMMENDATIONS

This study analyzed the economic efficiency of maize farmers in Dera Ismail Khan (D.I. Khan) and Bannu districts of Khyber Pakhtunkhwa, using data from 100 respondents. In D.I. Khan, which has a total area of 730,575 hectares, only 29.81% is cultivated—predominantly irrigated land. The district contributes 0.39% to the provincial maize area and 0.52% to production, with maize, dates, and mangoes as its key crops. In contrast, Bannu has a smaller total area (118,823 hectares), but a higher share of cultivated land at 62.64%, producing mainly wheat, maize, barley, and vegetables. Bannu accounts for 1.08% of the maize area and 1.21% of its production in the province.

In terms of profitability, D.I. Khan recorded an average maize yield of 824 kg per acre, with gross revenue of Rs. 108,692 and a net return of Rs. 26,898. Bannu followed with a yield of 736 kg per acre, gross revenue of Rs. 99,593, and net return of Rs. 22,166. Per-acre land rent was higher in D.I. Khan (Rs. 29,700) compared to Bannu (Rs. 27,830), while labor use was slightly lower in D.I. Khan (10.84 days) than in Bannu (11.1 days). DAP fertilizer use was equal in both districts, averaging 38.7 kg per acre.

Efficiency analysis revealed that technical efficiency was 0.59 in D.I. Khan and 0.52 in Bannu, suggesting that farmers could potentially increase maize output by 41–48% using existing resources more effectively. Allocative efficiency stood at 0.57 in D.I. Khan and 0.60 in Bannu, indicating a moderate capacity to optimize input use relative to costs. Economic efficiency, however, was low in both districts—0.33 in D.I. Khan and 0.31 in Bannu—falling below the overall average of 0.32, highlighting inefficiencies in both production and resource allocation.

Key cost drivers included DAP fertilizer, land rent, and labor. Although hybrid maize seeds were generally more profitable, their adoption in these districts remained limited. The study also found that education, farming experience, and off-farm income significantly improved efficiency levels, while weather factors—such as temperature and rainfall—had a measurable impact on technical efficiency, particularly in rainfed farming areas.

In developing countries like Pakistan, agricultural policy has traditionally relied on quantitative analyses to assess productivity, input efficiency, and farmer behavior. These studies offer critical insights for evidence-based policymaking and help identify inefficiencies to improve resource allocation (Hussain, 2004; Bravo-Ureta & Pinheiro, 1997; Ellis, 1998). A study on maize production in Khyber Pakhtunkhwa revealed that inputs such as seed, labor, fertilizers, and irrigation significantly influence yield. Recommendations include farmer education on input management, engaging experienced farmers, and improving access to training, extension services, and rural infrastructure. Factors like age, education, and off-farm income were linked to inefficiencies; thus, policies should also promote record-keeping and provide better pricing, timely payments, and credit facilities. The study emphasizes modernizing traditional practices through extension services and improving data collection for policy formulation. However, it faced limitations due to a small, localized sample, lack of record-keeping, and focus on a single crop. It also excluded factors like market risks and annual variability. Future research should expand to multi-crop systems, apply panel data, explore input-output price dynamics, and consider regional socio-economic variations. These steps would support more effective agricultural policies and enhance the productivity and sustainability of maize farming.

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