Estimation of Economic Efficiency of Maize Growers in Northern Khyber Pakhtunkhwa, Pakistan

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Abstract

This study evaluates the economic efficiency of maize growers in Northern Khyber Pakhtunkhwa, Pakistan, with a focus on the two districts of Swat and Buner. A total of 100 maize farmers (50 from each district) were selected using a multi-stage random sampling technique. Primary data were collected through a structured interview schedule. The analysis employed Cobb-Douglas type stochastic production and cost frontier models, estimated using Maximum Likelihood Estimation (MLE) in Stata software. The main production inputs included land, labor, seed, tractor hours, irrigation, urea, DAP, farmyard manure (FYM), and pesticides. Socioeconomic variables, including age, education, farming experience, family size, tenure status, off-farm income, and distance from farm to home, were considered in the inefficiency model. Additionally, climate risk variables — average maximum and minimum temperatures, and rainfall — were analyzed for their impact on technical efficiency. Results revealed that average yield and net return per acre were 680 kg and Rs. 22,437 in Swat, and 638 kg and Rs. 19,413 in Buner. Seed rate, labor, urea, DAP, FYM, and pesticides had significant positive effects on maize output. In contrast, cultivated area, tractor use, and irrigation were statistically insignificant due to their uniform use across terraced and hilly regions. The mean technical efficiency was 0.57, indicating that yields could be improved by 41% using current inputs more effectively. Among climate factors, higher maximum temperatures improved efficiency, while minimum temperatures increased inefficiency; rainfall had no significant effect. Allocative efficiency was 0.67 in Swat and 0.66 in Buner, suggesting potential cost reductions of 29% and 20%, respectively. However, overall economic efficiency remained low (0.32), with no farmer achieving full efficiency. To enhance performance, targeted interventions in farmer education, stakeholder collaboration, and pricing policy are essential, alongside district-specific policy support to address local socio-economic variations.

Keywords: Maize Production, Technical Efficiency, Allocative Efficiency, Economic Efficiency, Khyber Pakhtunkhwa, Pakistan.

Introduction

Agriculture remains the cornerstone of Pakistan's economy, driving food security, generating employment, reducing poverty, and contributing to 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. 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%), were key contributors to performance, supported by favourable prices,

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government policies, quality inputs, and timely credit. However, declines were observed in sugarcane and maize due to changes in cropping patterns. Recognizing agriculture's vital role, policymakers are increasingly focusing on enhancing efficiency rather than solely expanding inputs, particularly through the improved use of technology among small-scale farmers. This shift is crucial for improving productivity and rural livelihoods. Among staple cereals, maize, which is globally the third in cultivation after wheat and rice, holds great potential. In Pakistan, maize production is expanding; however, yield variations, particularly in provinces like Khyber Pakhtunkhwa, underscore 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 nationwide. 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 research and development (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 that resources are used cost-effectively. Combined, they form economic efficiency, a fundamental measure for sustainable agriculture.

Maize has long served as both a food and an 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 is used for food and seed. Despite its high nutritional and industrial value, the yield gap remains significant, with potential yield estimated at 7,184 kg/ha, while the actual average is just 4,425 kg/ha (GoP 2020).

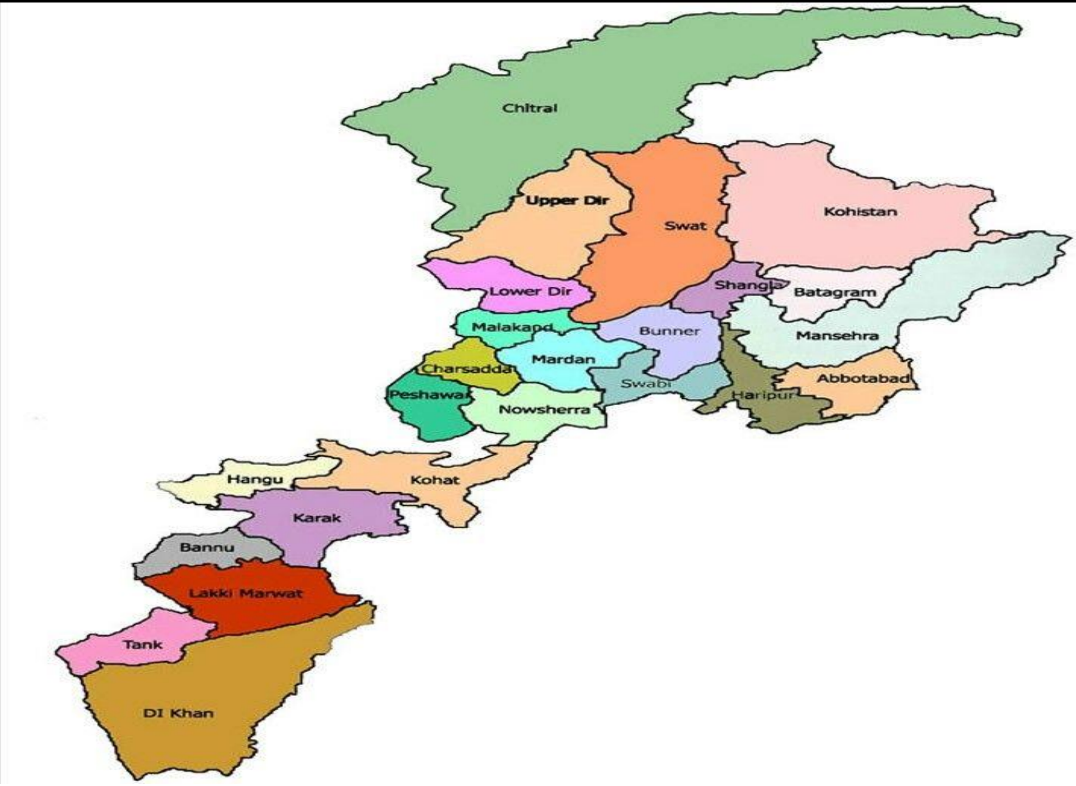
Khyber Pakhtunkhwa (KP) is a key maize-producing province, with Swat, Mardan, Mansehra, and Buner being major contributors to the industry. Yet, yields remain lower than their potential due to inefficiencies in input use and a lack of modern management practices.

This study focuses on evaluating the economic efficiency of maize production in the districts of Swat and Buner, located in the Northern 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.

Approach and Methods: Data Gathering and Modelling

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 Swat District, comprising 30 from the village of Madian and 20 from Beshigram, as well as 50 growers in Buner District, including 28 respondents from Nawagai and 22 from Kawga.

Figure 1: Map of Khyber Pakhtunkhwa province



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 sampled respondents. 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).

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 measurements. Frontier Approach can be broadly classified in two categories: parametric and non-parametric methods.

Per Acre Cost, Gross Revenue and Net Revenue of Maize Crop

The cost of inputs 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), pesticides, 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 and net revenues. 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).

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

$$Gri = P_i \times Y$$

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

Whereas;
P_i = Current market price for per unit of output
Y_i = Yield (Kg/Acre)
X_i = Quantity of inputs utilized by the i^{th} farmer
P_{xi} = Inputs prices
Here, NR_i represent the net revenue per acre, while GR_i refers to the gross revenue per acre for the i^{th} farm. Gross revenue is calculated by multiplying the yield per acre by the unit price of the output. TC_i represents the total cost of variable inputs, which includes expenditures incurred on the purchase of inputs.

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).

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.

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.

$$Y_i = f(A_k, B) \text{ expected } (-\mu_k) \qquad k = 1,2,3\ldots\ldots N \tag{2}$$

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, TE and frontier production of ki^{th} firm are depicted below:

$$Y_k = f(A_K, B) \tag{3}$$

$$TE_i = \frac{Yk}{Yk*} \tag{4}$$

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

$$= \exp(-\mu_k)$$

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 (B) 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 $\lambda > 0$. 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.

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).

$Y_j = f(A_j, B)\ \exp(v_j+\mu_j) \quad j = 1,2,3\ldots\ldots N$ (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).

Figure 2: Stochastic frontier production function

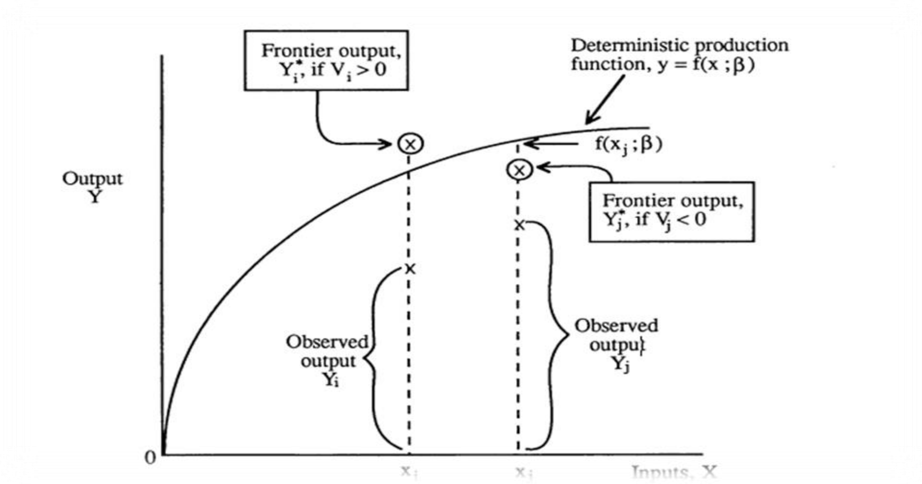


Figure 1 illustrates the core graphical concept of the stochastic frontier function, as described in equation (5), by comparing two producer firms, ith and jth. Firm ith, using input vector Xi, produces output Yi that exceeds the deterministic frontier output Yi* (f(Xi, β)), due to favorable conditions, resulting in a positive random error (Vi). In contrast, firm jth, with input Xj, produces Yj, which is lower than the frontier output f(Xj, β), reflecting unfavorable conditions and a negative Vi. Although both firms' outputs fall below the theoretical frontier, the unobservable production frontier is expected to closely follow the deterministic 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) = Yί / Y*ί (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., $Yí / Y^*í > (Yí / f(Xí, \beta)$

Firm "j[th]" experiences less adverse conditions (i.e., $Vj < 0$) within the stochastic frontier compared to the deterministic function $f(Xj, \beta)$, 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.

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 8 and 9.

$$Y_i = f(A_i, \beta) \qquad (i = 1,2\ldots n) \tag{8}$$

$$Y_i = \beta_o + \beta_i A_i + \varepsilon_i \tag{9}$$

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 (N̴~ (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).

Techniques to Estimate

Estimating production functions and exploring "duality theory" which links production and cost functions is a key focus in applied econometrics. Typically, Least Squares or Correlated Ordinary Least Squares (COLS) methods are used under the assumption of normally distributed error terms. However, the suitability of the estimation technique depends on the characteristics of the data and the error term distribution. The Frontier Production Approach can be estimated using either COLS or Maximum Likelihood Estimation (MLE). In cases of asymmetric error distributions, MLE is preferred, as it provides more accurate and asymptotically efficient results, as noted by Greene (1980). Therefore, MLE is adopted for this study.

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)

$$AE_i = {}^{Exp_i^*}\!\big/_{Exp_i} \tag{13}$$

Whereas:

AE_i = Represent allocative efficiency of í[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)

$$\text{Allocative inefficiency (AI)} = 1 - AE \quad (14)$$

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

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).

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

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

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.

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).

$$EE = TE*AE \quad (16)$$

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

Result & Discussion

Descriptive Statistics

Descriptive statistics summarize key features of maize growers' data, highlighting central tendency, variability, and range per acre. Table 1 presents mean, standard deviation, minimum, and maximum values, forming a foundation for further stochastic frontier analysis.

Table 1 presents the descriptive statistics of key inputs used by maize growers in district Swat. The average maize yield per acre was 680.2 kg, with a range from 480 to 920 kg and a standard deviation of 161.61 kg, indicating notable variability in production. The mean cultivated area was 2.37 acres, ranging from 1 to 10 acres, with a standard deviation of 1.69. Labor input averaged 8.6 man-days per acre, with a range of 2 to 16 and a standard deviation of 2.21. The average seed rate was 12.28 kg per acre, with a standard deviation of 3.33 kg and a range of 7 to 17 kg. Tractor usage averaged 1.61 hours per acre, ranging from 1 to 3 hours, with a relatively low variability (standard deviation 0.64). Irrigation applications averaged 4.11 per acre, ranging from 3 to 5, with a standard deviation of 0.90. In terms of fertilizer use, the average application rates of Urea and DAP were 77.50 kg and 46.38 kg per acre, with standard deviations of 25.88 kg and 13.54 kg, respectively. Urea application ranged from 25 to 100 kg, and DAP from 29 to 71 kg per acre. There was substantial variability in the use of pesticides and farmyard manure (FYM). The average pesticide use was 3000 ml per acre (range: 2500–5000 ml), with a standard deviation of 749.99 ml. FYM application averaged 267 kg per acre, ranging from 50 to 600 kg, with a standard deviation of 129.32 kg.

In Buner district, the average maize yield per acre was 638.20 kg, with yields ranging from 520 to 730 kg and a standard deviation of 62.37 kg, indicating moderate variability in production. The average land allocated for maize cultivation was 2.63 acres, with a range from 1 to 4 acres and a standard deviation of 2.21 acres. Labor input averaged 9.52 man-days per acre, ranging from 8 to 15 days, with a standard deviation of 1.69. The average seed rate was 11.02 kg per acre, with a standard deviation of 3.48 kg and values ranging from 7 to 17 kg. Tractor usage averaged 1.37 hours per acre, with minimal variability (standard deviation 0.54) and usage ranging between 1 and 3 hours. On average, 4.18 irrigation applications were made per acre, ranging from 3 to 5, with a standard deviation of 0.80. Fertilizer usage showed that Urea and DAP were applied at average rates of 73 kg and 42.2 kg per acre, respectively. Urea application varied from 25 to 100 kg, with a standard deviation of 25.17 kg, while DAP ranged from 27 to 63 kg with a standard deviation of 11.43 kg. Substantial variation was observed in the use of farmyard manure (FYM) and pesticides. On average, 270 kg of FYM and 3,440 ml of pesticides were applied per acre. FYM ranged from 100 to 600 kg with a standard deviation of 109.62 kg, while pesticide application ranged from 2,500 to 4,500 ml with a standard deviation of 773.01 ml.

Table 1: Descriptive statistics of key explanatory variables

District	Variables	Unit	Mean	Std. Dev	Min	Max
Swat	Yield	Kg.	680.20	161.61	480	920
	Area	Acre	2.37	1.69	1	10
	Labor days	No.	8.60	2.21	2	16
	Seed	Kg.	12.28	3.33	7	17
	Tractor	Hour	1.61	0.64	1	3
	Irrigation	No.	4.11	0.90	3	5
	Urea	Kg.	77.50	25.88	25	100
	DAP	Kg.	46.38	13.54	29	71
	FYM	Kg.	267.00	130.00	50	600
	Pesticides	ML	3000.00	749.15	2500	5000
Buner	Yield	Kg.	638.20	62.37	520	730
	Area	Acre	2.63	2.21	1	4
	Labor days	No.	9.52	1.69	8	15
	Seed	Kg.	11.02	3.48	7	17
	Tractor	Hour	1.37	0.54	1	3
	Irrigation	No.	4.18	0.80	3	5
	Urea	Kg.	73.00	25.17	25	100
	DAP	Kg.	42.20	11.43	27	63
	FYM	Kg.	268.00	109.62	100	600
	Pesticides	ML	3120.00	773.01	2500	4500

Where: DAP, FYM, ML, No, Kg stand for Diammonium phosphate, Farmyard manure, milliliter, Number, Kilogram.

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 Swat (680 kg, Rs. 22,437/-),and District Buner (638 kg, Rs. 19,423/-). The finding are consistent with the results of Mannan (2001).

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

District	Item	Unit	Quantity	Price/Unit	Value (Rs.)
Swat	Yield/Acre	Kg.	680	104	70700
	By Product				22436
	G.R				93136
	T.C/Acre				70699
	N.R				22437
Buner	Yield/Acre	Kg.	638	105	67266
	By Product				23156
	G.R				90422
	T.C/Acre				71009
	N.R				19413

Where G.R= Gross revenue, T.C = Total cost and N.R = Net revenue.

Maximum likelihood estimates of Stochastic Frontier Cobb-Douglas Production Function

Table 3: Technical efficiency effect model

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	0.88^{ns}	0.381
Ln Tractor	Hour	β_3	0.000	0.000	0.04^{ns}	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	0.63^{ns}	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 =Nonsignificant)

Table 4: Technical inefficiency effect model

Constant	--	δ_0	8.235	3.888	2.12	0.034
Age	Year	δ_1	0.016	0.119	0.14^{ns}	0.891
Off-farm income	D	δ_2	- 0.691	0.384	$- 1.80^{ns}$	0.072
Tenurial status	D	δ_3	0.412	0.379	1.09^{ns}	0.277
F.H.D	Km	δ_4	- 0.412	0.243	$- 1.69^{ns}$	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	0.84^{ns}	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 =Nonsignificant)

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

Table 3 present the frequency distribution of allocative efficiency scores among the sampled farmers, based on the computations derived from Equation 3.20. In the Swat District, the allocative efficiency scores for maize producers vary from a low of 0.50 to a high of 0.94, with an average score of 0.67. This suggests that the typical producer has the opportunity to decrease costs by as much as 29%, equating to Rs. 20,503 per acre, to reach the maximum allocative efficiency level achieved by the most efficient farmers in the district. A significant portion of the respondents, 31 individuals (60%), fall within the efficiency range of 0.50 to 0.70, while 11 respondents (22%) are in the 0.70 to 0.80 range, and 5 respondents (10%) fall between 0.80 and 0.90. Furthermore, allocative inefficiency in the Swat District is highlighted by the fact that only 2 respondents (4%) have efficiency scores exceeding 0.90.

In the Buner district, the allocative efficiency scores for maize producers vary, with a minimum of 0.56 and a maximum of 0.82, resulting in an average score of 0.66. This indicates that the typical grower has the potential to decrease costs by up to 20%, equivalent to Rs. 14,202 per acre, in order to achieve the efficiency levels of the more successful farmers in the area. A significant majority of growers, 36 individuals (80%), fall within the efficiency score range of 0.50 to 0.70, while 11 (22%) and 3 (6%) are categorized in the ranges of 0.70 to 0.80 and 0.80 to 0.90, respectively. Additionally, no farmers in the Buner district exhibited allocative efficiency scores above 90%, indicating a critical issue of allocative inefficiency.

Table 5: 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**
Swat	**No.**	1	31	11	5	2	**0.67**	**0.5**	**0.94**
	%	2	62	22	10	4			
Buner	**No.**	0	36	11	3	0	**0.66**	**0.56**	**0.82**
	%	0	72	22	6	0			

Source: Author field data estimation through STATA

Conclusion

Swat and Buner, located in the Malakand Division of Khyber Pakhtunkhwa, are significant maize producing districts. Swat contributes 12.43% of the provincial maize area and 12.41%

of its production, while Buner contributes 10.57% and 5.66%, respectively. In terms of average maize yield per acre, Swat recorded 680 kg with a net return of Rs. 22,437, and Buner had the lowest with 638 kg and Rs. 19,423 in net returns. Swat's land rent was Rs. 29,000 per acre, while Buner had the lowest at Rs. 27,060. Labor use per acre was 8.6 days in Swat (lowest) and 9.52 in Buner. Average DAP fertilizer use was 46.38 kg in Swat and 42.2 kg in Buner.
Regarding efficiency scores:
The study's findings reveal that Swat and Buner are among the least technically efficient districts in maize production within Khyber Pakhtunkhwa. Swat reported a technical efficiency score of 0.48, while Buner recorded the lowest score at 0.45, indicating that maize growers in these districts could potentially increase their output by over 50% through more effective use of existing resources. These low technical efficiency levels suggest critical gaps in knowledge, resource management, or access to improved farming practices.
In contrast, both districts performed comparatively better in allocative efficiency, with Swat scoring 0.67 and Buner 0.66. This indicates that farmers in these areas are relatively efficient in minimizing input costs, possibly due to careful expenditure management or better awareness of input pricing. However, despite allocative efficiency, economic efficiency remains low, primarily due to poor technical performance, resulting in limited overall productivity and profitability.

Recommendations

As a result of the study findings, the following recommendations have been proposed to enhance the economic efficiency of maize production in the research study areas:

- Main inputs such as seed, labor, tractor hours, urea, DAP, FYM, pesticides, and irrigation significantly impact maize production. Educating farmers on proper application of these inputs can increase yield and reduce waste.
- Technical and allocative inefficiency decrease with age, experience, education, off-farm income, and shorter farm-to-home distances. Policies should encourage the involvement of experienced farmers and provide timely payments and fair pricing.
- Strengthening farmer education through training institutes, Farm Field Schools, extension services, and international exposure can enhance efficiency.
- Infrastructure improvements, including rural roads and input storage centers near farms, can reduce inefficiencies and improve access.
- Most farmers lack record-keeping habits. Short-term informal training and long-term formal education can encourage better farm management.
- Support measures should include access to high-yield seeds, inputs, credit, insurance, mechanization, market linkage, and sustainability incentives.

References

- Ahmad, B., Chaudhry, M. A., & Hussain, S. (1994). *Cost of producing major crops in the Punjab*. Department of Farm Management, University of Agriculture, Faisalabad, Pakistan.
- Ahmad, B., Bakhsh, K., Hassan, S., & Khokhar, S. B. (2003). *Economics of growing different summer vegetables*. Faculty of Agricultural Economics and Rural Sociology.
- Aigner, D. J., Lovell, C. A. K., & Schmidt, P. (1977). Formulation and estimation of stochastic production function models. *Journal of Econometrics, 6*, 21–37.
- Ali, S., Andaleeb, N., & Ali, A. (2019). Technical efficiency of wheat growers in District Swabi of Khyber Pakhtunkhwa, Pakistan. *Sarhad Journal of Agriculture, 35*(4).
- Battese, G. E. (1992). Frontier production function and technical efficiency: A survey of empirical applications in agricultural economics. *Agricultural Economics, 7*, 185–208.

- Battese, G. E., & Coelli, T. J. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics, 20*, 325–332.
- Battese, G. E., Malik, S. J., & Gill, M. A. (1996). An investigation of technical inefficiencies of production of wheat farmers in four districts of Pakistan. *Journal of Agricultural Economics, 47*, 37–49.
- Battese, G. E., Malik, S. J., & Broca, S. (1993). Production functions for wheat farmers in selected districts of Pakistan: An application of a stochastic frontier production function with time-varying inefficiency effects. *Pakistan Development Review, 32*, 233–268.
- Battese, G. H., & Corra, G. S. (1977). Estimation of a production frontier model: With application to the pastoral zone of Eastern Australia. *Australian Journal of Agricultural Economics, 21*, 169–179.
- Battese, G. E., & Coelli, T. J. (1988). Prediction of firm-level technical efficiencies with a generalized frontier production function for panel data. *Journal of Econometrics, 38*, 387–399.
- Battese, G. E., Malik, S. J., & Gill, M. A. (1986). An investigation of technical inefficiencies of production of wheat farmers in four districts of Pakistan. *Journal of Agricultural Economics, 47*, 37–49.
- Battese, G. E., Malik, S. J., & Broca, S. (1993). Production functions for wheat farmers in selected districts of Pakistan: An application of a stochastic frontier production function with time–varying inefficiency effects. *Pakistan Development Review, 32*, 233–268.
- Debertin, D. L. (2003). *Agricultural production economics*. Macmillan Publishing Company.
- Farrell, M. J. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society: Series A (Statistics in Society), 120*(3), 253–290.
- FAO. (2024). *FAOSTAT online statistical service*. https://www.fao.org/faostat
- Government of Khyber Pakhtunkhwa. (2016). *Climate Change Policy 2016*.
- Government of Pakistan. (2020). *Agricultural statistics of Pakistan*. Ministry of Food, Agriculture and Livestock, Economic Wing.
- Government of Pakistan. (2020). *Crop yield gap analysis of Pakistan 2020*. Planning and Research Department, Zarai Taraqiati Bank Limited (ZTBL).
- Government of Pakistan. (2024). *Economic survey 2023–24*. Ministry of Finance.
- Green, W. H. (1980). On the estimation of a flexible frontier production model. *Journal of Econometrics, 13*, 101–116.
- Greene, W. H. (1993). The econometric approach to efficiency analysis. In H. O. Fried, C. A. K. Lovell, & S. S. Schmidt (Eds.), *The measurement of productive efficiency: Techniques and applications* (pp. 68–119). Oxford University Press.
- Greene, W. H. (2008). The econometric approach to efficiency analysis. In H. O. Fried, C. A. K. Lovell, & S. S. Schmidt (Eds.), *The measurement of productive efficiency and productivity change* (pp. 92–250).
- Hussain, M., Hussain, Z., & Ashfaq, M. (2004). Land and water productivity in Pothwar Plateau. *Pakistan Journal of Water Resources, 8*(2), 43–48.
- Kumbhakar, K., & Bhattacharyya, A. (1992). Price distortions and resource use efficiency in Indian agriculture: A restricted profit function approach. *Review of Economics and Statistics, 74*.
- Kumbhakar, S. C., & Lovell, C. A. K. (2000). *Stochastic frontier analysis*. Cambridge University Press.
- Murtaza, S., Ali, S. A., Shah, M., Ahmad, M., Ullah, I., & Khan, J. (2020). Adoption of hybrid maize technology in District Mardan of Khyber Pakhtunkhwa, Pakistan. *Sarhad Journal of Agriculture, 36*(4), 1047–1053.