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TRANSIENT AND PERSISTENT TECHNICAL EFFICIENCY FOR MAJOR CROPS FARMING IN INDIA

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ABSTRACT:

For the production of crops, India has a broad agricultural sector. The best indicator of the health of farming is technical efficiency, which helps to maintain high levels of agricultural production. Aigner et al. (1977) and Meeusen and van den Broeck (1988) proposed stochastic frontier analysis (SFA), which is being used to evaluate a reliable measure of technical efficiency (1977). The advanced stochastic frontier analysis method developed by Colombi et al. (2014), Kumbhakar, Lien, and Hardaker (2014), and Tsionas and Kumbhakar (2014) is used in the current work. This method includes four error components and a multistage estimation procedure. The data was extracted from the Ministry of Agriculture and Farmers' Welfare's Comprehensive Cost of Cultivation Scheme (CCCS) for the period 2004–2019. The study will focus on four important crops: paddy, wheat, sugarcane, and maize. The study's conclusion is that short- and long-term errors at decision-making units result in differences in transient technical efficiency and persistent technical efficiency for each crop (DMU).

Highlights: The efficiency of the farm is lowered by adding additional labour, which lowers the farm's profitability. When compared to other crops, wheat has a very low persistent technical efficiency (68%); nonetheless, this low persistent technical efficiency suggests that there may be room for improvement through the adoption of structural reform at the farm level.

Keywords: Crop Farming, Technical Efficiency, Transient Technical and Persistent Technical Efficiency, Heterogeneity, Law of Returns

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1. INTRODUCTION

The production process is the core of economic analysis and results in demand fulfillment. It is subjected to maximizing output by using a given set of input and reducing expenditure on production without decreasing the optimal level of output. Agriculture, as we all know, is the backbone of modern civilization and provides food security. However, most developing countries, including India, are dealing with a declining agricultural share of total output. The major source of concern in Indian agriculture is the high cost of production, particularly since the era of the green revolution. The high cost of production in agriculture leads to a decrease in the profit share of the farmers. The use of input in the manufacturing process is a continuous process that runs from start to finish. The same thing would be applied in crop production, because optimal use of agricultural input must produce optimal levels of agricultural output.

Throughout the crop production process, which includes pre-harvest and post-harvest, input utilization at the farm level is carried out to optimize the level of agricultural output. This research paper is concerned with examining the technical efficiency of farming. Whereas, technical efficiency is associated with wastage of input, it can be estimated through a stochastic frontier production function, which was first developed by Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1977) based on Farrell's literary work in production. In this research paper, an examination of technical efficiency is taken for major crops production during the period of 2004–2019. This study is based on panel data analysis with time variant efficiencies across years and crops farming using four error component stochastic frontier analyses. Major crops such as paddy, wheat, maize, and sugarcane are selected as crop variables for this study.

2. Significance of Study

Wheat and paddy are the most important food grains in India, particularly in the plains. Maize is also produced at a large scale in India, and sugarcane is a commercial crop that contributes to a high amount of production. India is the world's second-largest wheat producer after China, followed by the United States, and the world's tenth-largest wheat exporter. In terms of the production of wheat in India, Uttar Pradesh is the top producer, sharing 33.35% of total wheat production, followed by Madhya Pradesh (18.18%), Punjab (16.33%), Haryana (11.01%), Rajasthan (10.12%), and Bihar (5.17%). These six states account for at least 92.16% of India's total wheat production. India is the world's second-largest producer of paddy, as well as the world's largest exporter of rice. West Bengal holds the first position in the production of rice with 13.36% in paddy production, followed by Uttar Pradesh (13.05%), Punjab (9.91%), Andhra Pradesh (7.28%), Orissa (7.03%), and Telangana (6.25%). These six states constitute 56.88% of the production of paddy at the national level. Maize is an important crop because it is consumed by billions of people as a staple food grain, feed, and industrial raw material. India is a major producer of maize as well as a consumer of the grain. The global pattern of maize consumption constituted 61% for feed, 17% for food, and 22% for industrial raw materials. Karnataka is the top producer of maize, sharing 13%, followed by Madhya Pradesh (12.43%),

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Kerala (12.17%), Telangana (9.16%), and Tamil Nadu (7.56%). The maize production of these five states accounts for 46.76% of the total maize production. India is also the second-largest producer of sugarcane after Brazil. Uttar Pradesh is the highest producer of sugarcane in all of India, followed by Maharashtra (18.71%), Karnataka (10.31%), Tamil Nadu (3.81%), and Bihar (3.67%). Sugarcane is highest productive crops at farm level, is very intensive in cropping pattern (FAOSTAT, 2019).

3. Review of Literature

Stochastic frontier analysis is a tool for examining efficiency, decaying productivity, and determinants of efficiency in agrarian holdings. The results of such tools provide appropriate policymaking guidance for researchers, and the government also makes favourable decisions to improve farm efficiency. For better implementation of agricultural policies, technical efficiency has numerous insights for evaluating the performance of farming. The frontier production function provides information about farm heterogeneity over time, such as climatic conditions, soil quality, irrigation facilities, labour availability, and holding size involved in various states, such that specific input use for crop production varies over time. Stochastic frontier analysis is basically suitable for cross-sectional data, but in recent years it has been used for panel data-based stochastic frontier analysis introduced by Cornwell, Schmidt, and Sickles (1990) and Kumbhakar (1990), which all decompose firm-specific inefficiency levels to change over time. Earlier, Greene (2005a, 2005b) developed an estimation procedure for separating heterogeneity from inefficiency. To overcome this problem, stochastic frontier analysis is to be used, with recent advancements by Colombi et al. (2014), Kumbhakar, Lien, and Hardaker (2014), and Tsionas and Kumbhakar (2014), which incorporate four error components and multistage estimation processes. The error component analysis exhibits resource use efficiency and farm performance in the short and long run (Kumbhakar, Lien, and Hardaker 2014; Lien, Kumbhakar, and Alem 2018).

Rationalization of inefficiency is a drastic problem for farming units because management inefficiency leads to a decrease in output during the crop season. The neoclassical theory of production ignored the inefficiency component of the production process, assuming rational producer behavior. Farm unit management of input utilization during ploughing pursues an eminence role for optimum output, but failure in input utilization management leads to inefficiency at the farm level in both the short and long run. Inefficiency due to unobserved heterogeneity (weather condition and soil quality) in the short run at farm level is associated with transient technical inefficiency, and long-run inefficiency is associated with persistent technical inefficiency due to structural changes at farm level (Førsund, 2015). The law of variable proportion and the law of scaled returns are applied to a panel data-based frontier production function, which exhibit short- and long-run inefficiencies, respectively. The stochastic frontier analysis (SFA) framework has multiple versions developed by distinguished researchers who have extended this model for various sectors of the economy (Parmeter & Kumbhakar, 2014; Kumbhakar et al., 2017). Preference in SFA assembles a special focus on decomposing inefficiency by incorporating four components: firm heterogeneity, persistent

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technical efficiency, transient technical efficiency and stochastic error (Colombi et al., 2014; Tsionas & Kumbhakar, 2014; Kumbhakar et al., 2014, 2015; Filippini & Greene, 2016; Minviel & Sipiläinen, 2018). In several ways, this model improves on the previously developed model, such as the fact that the farm effect embedded in persistent technical inefficiency has a perpetual effect on farm inefficiency. Second, the premise of time-varying inefficiency is unaffected by previous levels of inefficiency, implying that farmers should learn from their previous levels of inefficiency and improve managerial skills in order to eliminate short-run deficiencies in crop production at the farm.

The error terms are classified into four types: farm-specific time-invariant latent heterogeneity, time-invariant or persistent technical efficiency, time-varying (transient) technical efficiency, and stochastic error. The model of Kumbhakar, Lien, et al. (2014, 2015) is described as following:

$$\mathrm{y_{it}} = \alpha_0 + (\mathrm{x_{it}}; \beta) + \mu_{\mathrm{it}} + \nu_{\mathrm{it}} - \eta_{\mathrm{it}} - u_{\mathrm{it}} \qquad (1)$$

$u_{it} \sim$ iid $N^{+}(0, \sigma^2)$
$\eta_{it} \sim$ iid $N^{+}(0, \sigma^2)$
$\nu_{it} \sim$ iid $N(0, \sigma^2)$
$\mu_{it} \sim$ iid $N(0, \sigma^2)$

In this model, the main presumptions are that all error components are independently distributed from each other and the regressor. In the preceding equation (1), y_{it} is the quantity of crop production at i farm in year t, x_{it} is the vector of input utilization for crop production at i farm in year t, β lays down for the vector of technological parameter assigned with input, and μ_{it} seizes random effect heterogeneity at farm level, also known as farm effect. In the above model, there are four decompositions of error terms classified into two groups, such as, inefficiency index into u_{it} (time-varying transient technical) and η_{it} (time-invariant or persistent technical), and farm effect μ_{it} (time-invariant heterogeneity) and stochastic error term (v_{it}). The estimation of this model is hands-on with a multistage estimation process like:

$$\mathrm{y_{it}} = \alpha_0^* + (\mathrm{x_{it}}; \beta) + \alpha_i + \varepsilon_{it} \qquad (2)$$

$$\alpha_0^* = \alpha_0 - E(\eta_i) - (u_{it}) \qquad (3)$$

$$\alpha_i = \mu - \eta_i + E(\eta_i) \qquad (4)$$

$$\varepsilon_{it} = \nu_{it} - u_{it} + E(u_{it}) \qquad (5)$$

α_0^* is the coefficient of particular farmer obtained using equation (3), which α_0 is the time-constant error constituent (including the farm effect μ and the time-unchanging inefficiency element η_i). α_i and ε_{it} are assumed to have a constant mean and zero variance. Translog Production Function is specified in context of this model based on likelihood ratio tests over the Cobb Douglas production function.

$$y_{it} = \beta_0 + \sum_{i=1}^{n} \beta_1 lnX_{1it} + \sum_{i=2}^{n} \beta_2 lnX_{2it} + \frac{1}{2}\sum_{i=1}^{n}\sum_{i=2}^{n} \beta_3 lnX_{1it} lnX_{2it} + \frac{1}{2}\sum_{i=1}^{n} \beta_4 lnX_{1it} lnX_{1it} + \frac{1}{2}\sum_{i=2}^{n} \beta_5 lnX_{2it} lnX_{2it} + \mu_{\mathrm{it}} + \nu_{\mathrm{it}} - \eta_{\mathrm{it}} - u_{\mathrm{it}} \qquad (6)$$

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Here y_{it} is per hectare crop production at i farm in t time period, β is coefficient parameter, X_1 and X_2 is input used in production process. $\mu_{it}, \nu_{it}, \eta_{it}, and\ u_{it}$, all are previously defined.

4. Data and Variables:

The Ministry of Agriculture and Farmers' Welfare under the Department of Economics and Statistics has collected data on the cost of cultivation for different crops produced across India. The Comprehensive Cost of Cultivation Scheme (CCCS) of Major Crops collects data at farm level. This study seeks to estimate efficiency for per-hectare crop production at the farm level for major crops across India. Collected data is identified as quantities of input and output in the production process. Quantity of inputs such as labour hours/h, machinery cost/hectare as a proxy variable, amount of fertilizers in kg/h, manure in quintal/h, seed in kg/h, and bullock hour are considered for the estimation process.

Table: 1 Summary Statistics for Production Function at Indian Farm

Variables	Observations	Mean	Std. Dev.	Min	Max
Crop Production (Kg/Hectare)	782	13001.05	25333.98	686	113538
Seed (Kg/Hectare)	782	55.15048	48.28018	14	341.56
Fertilizer (Kg/Hectare)	782	128.636	128.2559	76	724.82
Manure (Quintal/Hectare)	782	32.28059	45.84918	0	315.13
Human Labor (Hour/ Hectare)	782	525.9714	538.9627	6.25	2631.84
Bullock (Hour/ Hectare)	782	49.11875	53.20696	4	394.27
Machinery Used (Hour/ Hectare)	782	3698.455	3313.135	765	26071.4

5. Results and Discussion

The Translog production function incorporates input utilization flexibility, particularly with reference to time period. There are five inputs used: seed in kg, fertilizer in kg, manure in quintal, bullock hour, labour hour and machine cost in rupees, chosen for all four crops such as paddy, wheat, sugarcane, and maize represented in Table 1. Four error components based on

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stochastic frontier analysis decay productive efficiency into persistent technical efficiency and transient technical efficiency. Fertilizer is significant at a 10% level for per hectare paddy production; driving a 1 unit increase in fertilizer utilization at the farm increases per hectare total production by 0.594 unit. For per-hectare wheat production, seed, manure, bullocks, and human labour are significant at 5%, 10%, 5%, and 1%, respectively. The findings indicate that increasing farm labour resulted in inefficient farming. Increase in 1 unit utilization of human labour in wheat farming declined by 0.764 units in per hectare production. For sugarcane farming, seed and manure are significant at the 1 % and 10%. Seed, in particular, is an important input for sugarcane production, with a one unit increase in seed resulting in 0.665 units increase in sugarcane production per hectare. Maize, a staple food, is also an important crop in India. Per hectare production of maize is highly influenced by labour and machinery, which are significant at a 5% to 10% level. The results show that more assigned human labour in maize farming reduces per hectare production, whereas the use of machines in maize farming increases per hectare production. The combined production of these four crops enables efficient farming, in which seed, fertilizer, and machine use are used as inputs at the farm level. However, human labour is a negative indicator in all four crops because adding more human labour to farming does not increase per-hectare crop production.

Table 2: Estimation of Translog Production Function

lnyieldkg					
Variables	Paddy	Wheat	Sugarcane	Maize	Combined
lnseed	0.0306 (0.204)	0.176** (0.080)	0.665*** (.1536)	0.785 (0.841)	0.399 (0.372)
lnfertilizer	0.594* (0.314)	0.019 (0.693)	0.288 (0.868)	0.870 (0.963)	0.744*** (0.095)
lnmanure	-0.0243 (0.187)	-0.390* (0.220)	0.334* (0.213)	-0.00210 (0.630)	0.513** (0.227)
lnhuman	-0.198 (0.183)	-0.764*** (0.078)	-0.148 (0.444)	-0.396** (0.183)	-0.0866 (0.332)
lnbullock	-0.434*** (0.166)	-0.700** (0.282)	0.871 (0.895)	0.831 (0.068)	-0.549** (0.231)
lnmachine	0.125 (0.137)	0.792 (0.517)	0.824 (0.719)	0.572* (0.365)	0.9467*** (0.270)
lnseed*lnfertilizer	0.0369 (0.124)	0.941*** (0.169)	0.462 (0.615)	0.985 (0.743)	0.420*** (0.129)
lnseed*lnmanure	0.0160 (0.0628)	0.284** (0.127)	-0.0331 (0.176)	-0.202 (0.176)	0.0413 (0.0342)
lnseed*lnhuman	-0.0590 (0.0749)	0.525 (0.682)	0.912*** (0.160)	0.837 (0.981)	0.0917 (0.0798)
lnseed*lnbullock	0.0507 (0.0502)	0.0124 (0.154)	-0.296 (0.233)	-0.512 (0.348)	-0.119** (0.0462)
lnseed*lnmachine	0.0421 (0.0537)	0.853*** (0.301)	0.249 (0.219)	-0.586 (0.360)	0.0792 (0.0781)

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lnfertilizer*lnmanure	0.0469 (0.0904)	-0.0253 (0.0730)	-0.195 (0.443)	-0.122 (0.0907)	-0.135* (0.0698)
lnfertilizer*lnhuman	-0.147 (0.129)	-0.302*** (0.099)	0.0606 (1.432)	0.446 (0.675)	0.296 (0.183)
lnfertilizer*lnbullock	0.0500 (0.0834)	0.202 (0.140)	0.0370 (0.499)	-0.0944 (0.126)	-0.152* (0.0916)
lnfertilizer*lnmachine	0.233*** (0.0719)	0.133 (0.243)	0.998** (0.442)	0.0436 (0.326)	0.0579 (0.109)
lnmanur*lnhuman	-0.0636 (0.0555)	-0.0794 (0.0710)	-0.660* (0.360)	0.165 (0.162)	0.0606 (0.0512)
lnmanure*lnbullock	-0.00268 (0.0325)	0.0322** (0.0161)	-0.0198 (0.159)	0.0186 (0.0376)	0.00257 (0.0206)
lnmanure*lnmachine	0.0362 (0.0467)	-0.00610 (0.0363)	0.173 (0.150)	0.0207 (0.0581)	-0.0982** (0.0431)
lnhuman*lnbullock	-0.0589 (0.0454)	-0.152** (0.0753)	-0.525 (0.614)	-0.0974 (0.288)	-0.144** (0.0633)
lnhuman*lnmachine	0.0911* (0.0477)	0.468*** (0.178)	0.323*** (0.071)	0.650 (0.445)	0.370*** (0.0779)
lnbullock*lnmachine	-0.117*** (0.0375)	0.141** (0.0616)	-0.0614 (0.173)	0.108 (0.0849)	0.367*** (0.0414)
lnseed*lnseed	0.0610* (0.0311)	0.230** (0.090)	0.343 (0.208)	0.156 (0.684)	0.0411 (0.0501)
lnfertilizer* lnfertilizer	0.151 (0.102)	0.383 (0.269)	0.698 (1.026)	0.201 (0.401)	0.772*** (0.136)
lnmanure*lnmanure	-0.0256 (0.0270)	0.00816 (0.00768)	0.273*** (0.0835)	-0.0157 (0.0120)	0.00279 (0.0122)
lnhuman*lnhuman	0.0774 (0.0498)	0.258 (0.205)	0.682 (0.724)	-0.986 (0.756)	0.226*** (0.0761)
lnbullock*lnbullock	0.0114 (0.0154)	0.00789 (0.0133)	0.238* (0.137)	0.0165 (0.0169)	-0.00370 (0.0147)
lnmachine*lnmachine	0.0377 (0.0271)	0.0261 (0.0629)	0.200*** (0.0693)	0.0459 (0.0964)	0.0398 (0.0381)
Constant	5.618*** (0.759)	16.44*** (3.225)	7.168 (28.75)	34.78* (19.42)	10.41*** (1.600)
sigma_u	.31061006	.35792623	.18862918	.33882986	.25956232
sigma_e	.12267052	.11229609	.27315097	.1628793	.44604042
Rho	.86507213	.91038751	.32289851	.81229276	.25297169
R-squared	0.509	0.604	0.516	0.680	0.848

Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

This study is associated with unbalanced panel data used for 782 farm level data sets across 2004–2019 in all of India. In which farm data is divided into 291 paddy farm data, 203 wheat farm data, 112 sugarcane farm data, and 176 maize farm data. The estimation findings

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for the SF model of persistent technical efficiency and transitory technical efficiency for paddy, wheat, sugarcane, and maize are shown in Tables 3. Using Comprehensive Cost of Cultivation scheme (hereafter, CCCS) data for the entire period 2004–2019, efficiency estimates for persistent technical efficiency, transient technical efficiency, and overall technical efficiency are generated. The combined CCCS data results revealed that the mean persistent technical efficiency (0.99) and mean transient technical efficiency (0.77), both of which are assessed in Indian farm for crop productivity. Despite estimates of transient technical efficiency showing lower minimum values when compared to estimates of persistent technical efficiency and greater variation across farms, this reflects greater diversity and the potential for transient technical efficiency gains across farms (see Table 3 and Figure 1, 2, and 3). Relationships between agricultural efficiency and time periods are typically found in scatter plots. We are interested in learning what a reasonable vertical farm efficiency projection would be in these circumstances given a particular horizontal time period. Farm efficiency is broken down into three categories: overall technical efficiency, transient technical efficiency, and persistent technical efficiency. There is a connection between the combined technical efficiency of paddy, wheat, sugarcane, and maize.

Generally speaking, mean overall technical efficiency was estimated to be 0.77. According to research by Kumbhakar, Lien, et al. (2014), persistent efficiency (0.71) for grain farms in Norway between 2004 and 2008 was worse than residual efficiency (0.89), demonstrating that addressing persistent inefficiency should occur first in order to prevent long-term issues. Similar findings were exhibited for Swedish dairy farms between 1976 and 1988, when the transient technical efficiency (0.93) was higher than the persistent technical efficiency (0.90) (Kumbhakar and Heshmati, 1995). Instead, in situations of considerable chronic inefficiency for wheat production, a farm is expected to operate with a relatively high level of efficiency over time, barring changes in management or policy (Kumbhakar et al., 2015). It is critical from a policy perspective to differentiate between persistent and transient inefficiency since each policy has a unique set of consequences that may be employed to alleviate inefficiency. The mean overall technical efficiency indicates joint effect of natural condition and farm management, is for paddy 0.916, for wheat 0.637, sugarcane 0.813, and for maize 0.992. At the farm level, the combined mean overall technical efficiency of these four crops is 0.77. Per hectare, wheat production has recorded the lowest mean overall technical efficiency (0.63), and maize has recorded the highest mean overall technical efficiency, 0.992.

According to the estimated efficiency scores, the mean transient technical efficiency (0.93) for wheat is higher than the mean persistent technical efficiency (0.68), indicating more potential for production improvement by removing structural causes of technical inefficiency rather than focusing on the transient factors. This is an important discovery because unplanned, uncontrollable occurrences like pest outbreaks and severe weather, among other factors, may create transient inefficiency. From the above discussion, it is quite clear that the persistent technical efficiency shows favourable conditions for paddy, sugarcane, and maize, but wheat records the lowest mean persistent technical efficiency, 68%, meaning there is potential improvement at farm level by adaption of technological innovation and reorganization of farm

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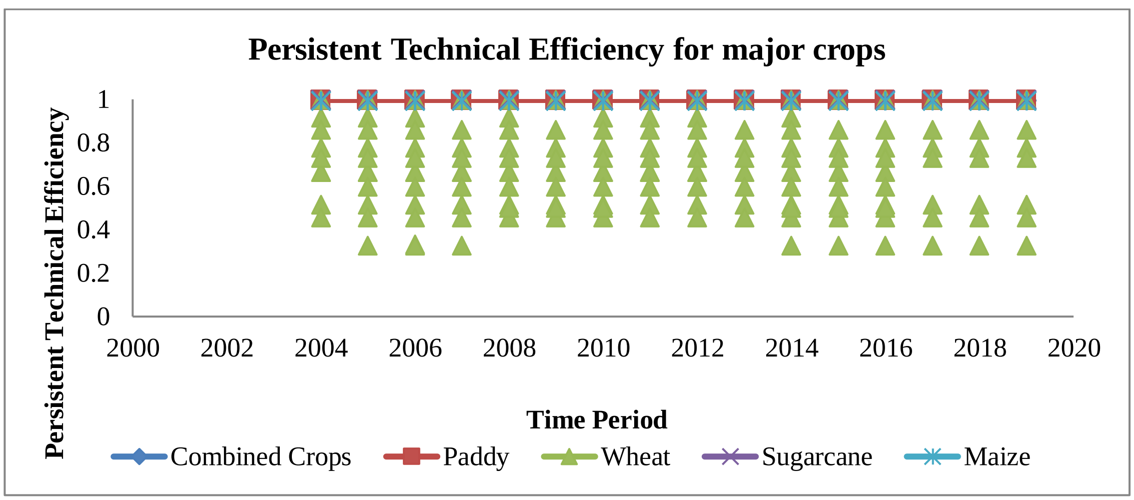
unit etc. It seems that there is no potential improvement in persistent technical efficiency of paddy, sugarcane, or maize farming, but a high chance in wheat farming. From our analysis, one thing is clear, transient technical efficiency is still challenged for crop production, especially in sugarcane production. Mean transient technical efficiency is reported to be very low at the national level (77% in crop production). Transient technical inefficiency in farming is a difficult task for farmers because it is associated with an uncontrollable effect, such as an unfavorable natural condition and soil quality at the farm level. So, from our perspective, the government should address the issue of transient technical efficiency to increasing per hectare crop production.

Table 3: Estimation of Persistent technical, transient technical and overall technical efficiency

Efficiencies variable	Paddy	Wheat	Sugarcane	Maize	Combined
Mean Persistent technical Efficiency	.997	.682	.999	.994	.998
Mean Transient technical Efficiency	.919	.933	.814	.998	.772
Mean Overall Technical Efficiency	.916	.637	.813	.992	.77

Scatter Plot: Figure 1



Scatter Plot: Figure 2

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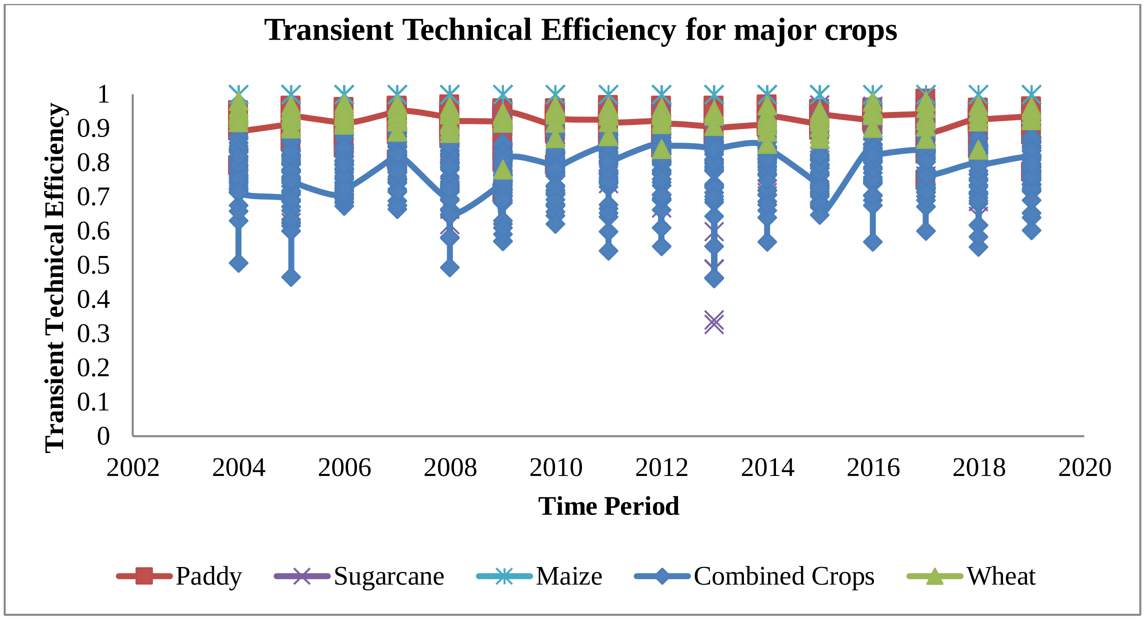
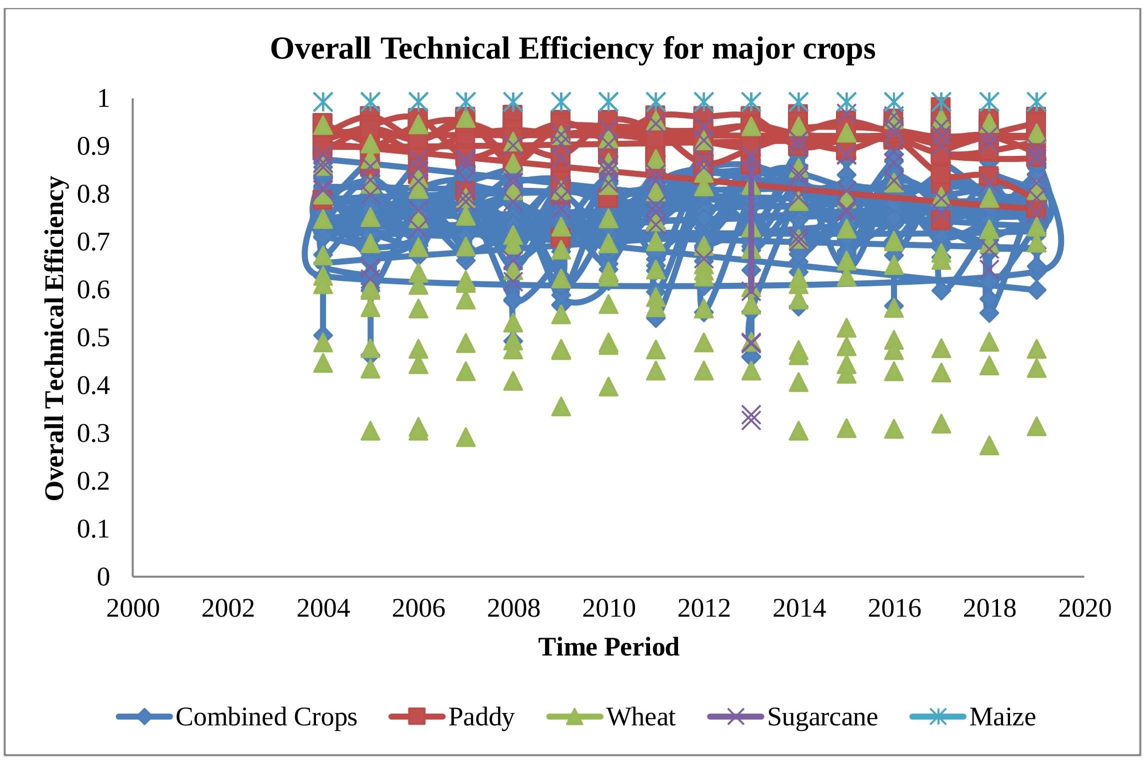


Scatter Plot: Figure 3



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6. CONCLUSION:

The above discussion is limited to farm input utilization. Efficiency estimation is divided into two categories: transient technical efficiency, which refers to natural farming conditions, and persistent technical efficiency, farm management, which indicates how efficiently input is used by the farmer at their decision-making unit. Natural conditions like soil quality, natural calamities, temperature, and annual rainfall are different across the country. Farm management is also associated with natural conditions regarding input utilization for different crops' production. From above, different climate conditions and soil quality also affect overall technical efficiency.

We find that the mean transient technical efficiency (0.93) for wheat is higher than the mean persistent technical efficiency (0.68), indicating more room for production improvement by addressing structural reasons of technical efficiency rather than concentrating on the transient components. It is noteworthy that the mean overall technical efficiency score found for wheat (0.63) is lower than the corresponding score of paddy, sugarcane, and Maize, 0.91, 0.81, 0.99, respectively. Our findings advocate for a restructuring the policy of wheat farming towards more targeted initiatives, such as infrastructure improvement, extension, and, most importantly, innovation promotion, in order to support the reallocation of farm resources to more productive uses in response to new technologies. Additional research on additional phenomena, such as the outcomes of rural development programmes and policies, work by advisory services, etc., with a potential cumulative impact on farm efficiency, could be very important, especially for the appraisal of developing and implementing policies and upcoming changes to policy instruments. It may also be intriguing to observe how potential time-varying factors affect the time-varying transient technical efficiency component as this study only considered the persistent technical efficiency component.

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