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# Regional technical efficiency and technology gap differences: The empirical evidence from rice farms in Bangladesh

Md Abdus Salam
*Department of Agricultural Economics, Bangabandhu Sheikh Mujibur Rahman Agricultural University*

## Abstract

Using the stochastic meta-frontier approach, this study compares the technical efficiency (TE) and technology gap ratio (TGR) of different climate sub-regions in Bangladesh with heterogeneous technology adoption among rice farmers using nationally representative cross-sectional data from 13,113 rice plots across all climatic sub-zones. This particular method enabled the calculation of comparable TE and TGR for rice farms operating under different technologies. Empirical results shows that the mean TE ranged from 68% to 78% across the climatic zones. Accordingly, the farmers in the northwestern zone were the most technically efficient (78%) and had the highest mean TGR (83%), implying that these farmers adopted the most advanced technologies. Contrastingly, the farmers in the southeastern zone had the lowest adoption of advanced technology. Moreover, this study found that household head age, education, land ownership, and agriculture as major income are the major drivers of TE. Increasing investment in research and development, strong extension services including farmer training need to diffuse climate zone-specific technologies, crop management practices, and efficient use of resources at the farm level. However, the diversity of characteristics of region explains the use of various types of production technologies, resulting in a technology gap that slows the economic convergence of these regions.

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**Contact:** Md Abdus Salam - salamecon@bsmrau.edu.bd.
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# 1. Introduction

Rice is the primary staple food in Bangladesh. In a global context, Bangladesh is the most densely populated country, and its agriculture sector is the pillar of the food and livelihood security of its ever-growing population. The contribution of this sector is approximately 14.23% of the gross domestic product (GDP) and employs approximately 40.60% of the total labor force in Bangladesh (BBS, 2019). However, the population of Bangladesh continues to grow by two million every year; thus, the additional population will require additional food; hence, the rice yield must be increased by adopting advanced technologies and reducing the technological gap across the climatic sub-zones (Bangladesh Rice Knowledge Bank). Bangladesh's overall rice production and technical efficiency (TE) are affected by considerable regional differences (Bäckman, *et al.* 2011) such as environmental conditions, farming practices, and techniques, availability of irrigation, farmers' economic conditions, etc. The country has seven climatic sub-regions, each having distinct economic and environmental conditions and resource endowments (Sarker *et al.* 2019). For instance, there are differences within and between zones in soil quality, water availability, temperature, rainfall, water salinity, humidity, farmers' socioeconomic resource base, and the composition of inputs. Consequently, not all farmers can equally access globally available technologies. Farms in various regions select from various sets of probable input-output combinations for their specific production opportunities and situations (Alem *et al.* 2019). Consequently, comparing farms' performance in various climate zones using TE scores calculated from sole estimates across all climate zones may produce confusing results as benchmarks for distinct farms and as basis for policy interventions (Kumbhakar *et al.* 2015). Given these backdrops, farmers across the climate zones might be incapable to achieve high productivity levels because of the physical constraints imputed by their production environments and different farmers' economic capabilities to achieve higher productivity. This study intends to investigate the significance of regional technical efficiency and technology gap differences of rice farms across the subregions of Bangladesh. Specifically study will be addressing the determining frontiers and the metafrontier specific to each region and assessing the level of technological gap among the regions. This article will help test the technological gap catch-up hypothesis among the sub-regions of Bangladesh with a low level of technology and the ones with a high one.

Moreover, different research institutes in Bangladesh have developed region-and season-specific high-yielding rice varieties that make it interesting to study potential regional TE and technology gap ratio (TGR) differences. For example, the Bangladesh Integrated Household Survey 2015 (BIHS2015) indicates that the rice yield in the western zone is 67% higher than in the southeastern zone; notably, farmers in the western zone use more than double the fertilizer compared to the southeastern zone. Understanding the regional level rice production performance could assist policymakers to introduce suitable agricultural policies and systems for sustainable development. Many studies have examined the TE and technology gap in different countries using the stochastic meta-frontier approach. This method was first introduced by Hayami (1969) and Hayami and Ruttan (1971) to assess efficiency, based on the hypothesis that farms in different agro-ecological zones have access to the same technology (O'Donnell, Rao, and Battese, 2008). However, stochastic meta-frontier frequently involves regional or group studies to analyze the TE and TGR in different aspects. For example, Mariano *et al.* (2011), Alem *et al.* (2019), and Gero (2020) examined the regional differences in TE and TGR; Uddin *et al.* (2014), Anang *et al.* (2017), and Bravo-Ureta *et al.* (2020) examined the farm's performance under different production systems by using stochastic meta-frontier analysis. In the case of Bangladesh, several studies estimated the TE (e.g., Hasnain *et al.* 2015; Jalilov *et al.* 2019; Anwar *et al.* 2021) of rice farms, but the available literature did not compare the TE and technology gap among the climatic subregions in Bangladesh. So, this study focused on the TE and TGR differences among the subregions by applying a stochastic meta-frontier approach using the latest rural household survey data. Accordingly, this approach provided new evidence on the TE and technology gaps across the seven climate subregions in Bangladesh.

# 2. Analytical framework

## 2.1 Study area coverage

Rice production depends on environmental conditions such as rainfall, temperature, and water sources, which can differ among climate zones, production seasons, etc. We decomposed total factor productivity (TFP) into the TE and TGR for farmers in seven climatic zones that might use various production technologies according to climatic conditions. The climatic conditions were geographically classified into seven climatic sub-zones in Bangladesh [Fig. 1; Sarker *et al.* (2019)]. The major distinguishing features of the seven climatic subregions are listed in Table 1.

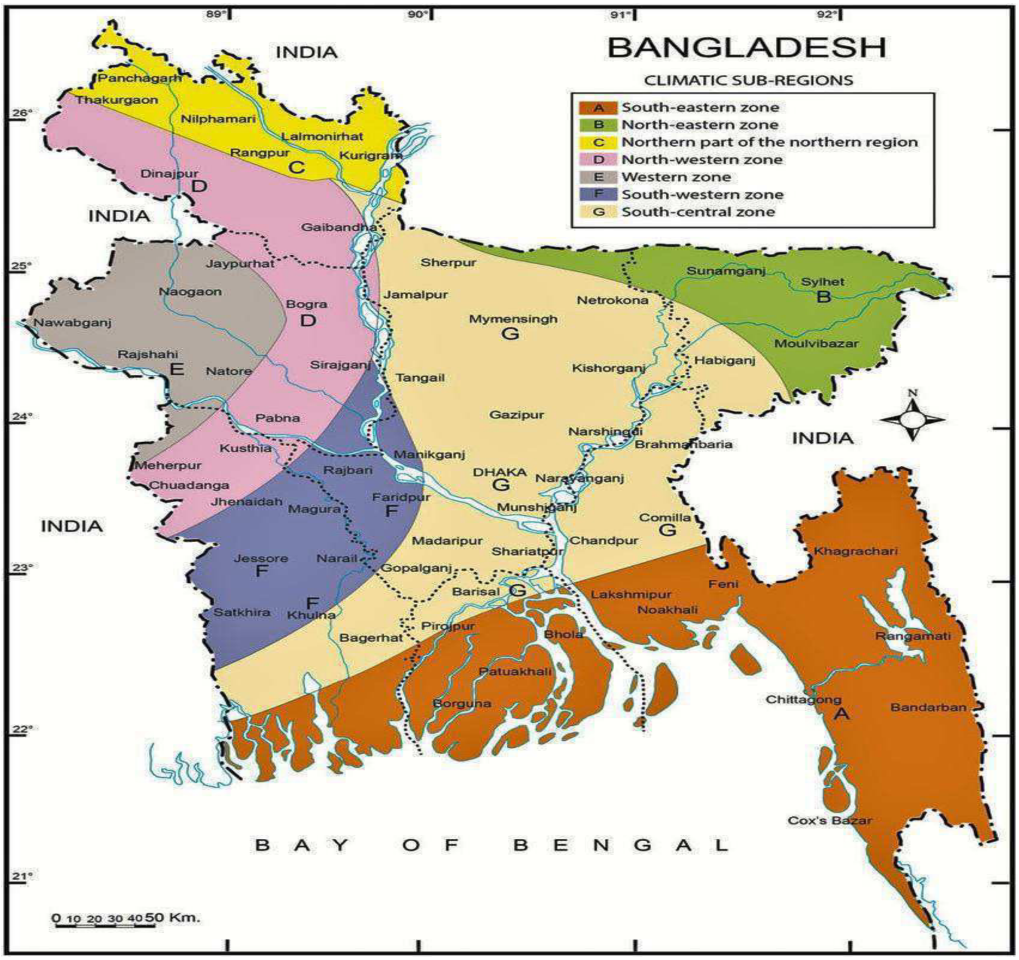


**Figure 1.** Climate zones of Bangladesh. Source: Sarker *et al.* (2019)

**Table 1.** Major characteristics of the climatic sub-regions

| Name of climate zone | Major characteristics |
|---|---|
| Southeastern | Hilly area (height over 300 m); small range of temperature; heavy rainfall (usually over 2,540 mm); and high cyclone risk. |
| Northeastern | Mild summer temperature; average humidity (relatively higher than the southeastern zone); fog in winter; cloudiest part of Bangladesh; and moderate cyclone and cold wave risk. |
| Northern part of the northern region | Heavy rainfall (2,000 to 3,000 mm); hot summer temperatures; and cold in winter, high cold wave risk. |
| Northwestern | Moderate rainfall and hot summer temperatures. |
| Western zone | Driest and hottest temperature in Bangladesh; low rainfall and summer humidity of less than 50%. |
| Southwestern | Fewer extremes with hot temperature and heavy rainfall; and moderate water salinity. |
| South-central zone | Mild summers and abundant rainfall. |

## 2.2 Empirical model

The farms operating under different climatic zones, the TE is not comparable under the same production frontier, as production units make choices among various combinations of input-output (Melo-Becerra and Orozco-Gallo 2017). Battese and Rao (2002) introduced a meta-frontier, followed by Alem *et al.* (2019) and Mariano *et al.* (2011) to estimate comparable group-wise TE under different technologies. Recently, Huang *et al.* (2014) introduced a new two-step technique using a stochastic frontier analysis (SFA) to estimate the specific group frontier estimation in the first step and the meta-frontier method in the second step. This study followed the two-step procedure by Huang *et al.* (2014), Jiang and Sharp (2015), and Melo-Becerra and Orozco-Gallo (2017) to estimate the TE and technological gap among the climatic zones of rice farms in Bangladesh, where TE is obtained from estimating a production frontier from each group and the meta-frontier using the Battese and Coelli (1995) approach. The general stochastic production frontier model is as follows:

$$Y_i^k = f^k\left(X_i^k, \beta^k\right) e^{V_i^k - U_i^k} \text{ where, } j = 1, 2, 3, 4 \dots . J; \;\; i = 1, 2, 3, 4, \dots N_j \qquad (1)$$

where $Y_i^k$ denotes the output of rice, $X_i^k$ represents the vector of inputs for the $i^{th}$ rice farm in the group of $k^{th}$, $\beta^k$ denote a vector of $k^{th}$ group's unknown parameter to be estimated. The term $V_i^k$ is the stochastic error term that is an independently and identically distributed ($iid$) random variable as $V_i^k \sim N(0, \sigma_{vk}^2)$ that captures the stochastic noise. The term $U_i^k$ is a one-sided error representing the technical inefficiency of farm $i$ and group $k$ and is assumed to be $iid$ as $U_i^k \sim N^+\left(0, \sigma_{uk}^2\left(Z_i^k\right)\right)$, where $Z_i^k$ represents the inefficiency variable. Thus, the inefficiency obtained from each production group model is associated with the inefficiency variables, $Z_i^k$ specific to each farm within the group, as defined:

$$TE_i^k = \frac{Y_i^k}{f^k(X_i^k, \beta^k) e^{V_i^k}} = \frac{f^k\left(X_i^k, \beta^k\right) e^{(-U_i^k)}}{f^k(X_i^k, \beta^k)} = e^{-U_i^k} \qquad (2)$$

where $TE_i^k$ indicates TE, which measures the each farm $i$ performance relative to the specific group frontier and the meta-frontier production function is defined as $f^M\left(X_i^k, \beta\right)$ that envelops all the k groups' frontiers $f^k\left(X_i^k, \beta^k\right)$ and is expressed as SFA following Huang *et al.* (2014) in the second step:

$$\hat{f}^k\left(X_i^k, \beta^k\right) = f^M\left(X_i^k, \beta\right) + V_i^M - U_i^M \qquad (3)$$

where $\hat{f}^k\left(X_i^k, \beta^k\right)$ denotes the prediction from the first step in (1) of specific group frontiers, which explains that the frontier prediction of individual groups is pooled together into one vector of the whole sample. The term $V_i^M$ denotes the error term and assumed to be $iid$ as $V_i^M \sim N(0, \sigma_{VM}^2)$ and the one-sided error term $U_i^M$ that represents technical inefficiency as $U_i^M \sim N^+(0, \sigma_{uM}^2(Z_i^M))$, where $Z_i^M$ represents the specific determinant for the technology-gap components, and β is the vector of the unknown parameter to be calculated for the meta-frontier. The term $U_i^M \geq 0$ and therefore $f^M(\cdot) \geq f^k(\cdot)$ and the relationship of the $k^{th}$ production frontier to the meta-frontier is defined as the TGR as follows:

$$TGR_i^k = \frac{f^k\left(X_i^k, \beta^k\right)}{f^M\left(X_i^k, \beta\right)} = e^{-U_i^M} \leq 1 \qquad (4)$$

According to Huang *et al.* (2014) and Alem *et al.* (2019), at a given level of inputs $X_i^k$, the observed output $Y_i^k$ of the $i^{th}$ farm relative to the meta-frontier ($\frac{Y_i^k}{f^M(X_i^k,\beta)}$) consists of three components: the technological gap ratio is defined as $TGR_i^k = \frac{f^k\left(X_i^k,\beta^k\right)}{f^M(X_i^k,\beta)}$, where the TE is represented as $TE_i^k = \frac{f^k\left(X_i^k,\beta^k\right)e^{\left(-U_i^k\right)}}{f^k(X_i^k,\beta^k)} = e^{-U_i^k}$ and the random noise component represents $e^{V_i^k} = \frac{Y_i^k}{f^M(X_i^k,\beta)e^{\left(-U_i^k\right)}}$. The TE of each unit of production with respect to the meta-frontier, the meta-frontier technical efficiency (MTE) is expressed as

$$MTE_i^k = \frac{Y_i^k}{f^M(X_i^k,\beta)e^{\left(V_i^k\right)}} = TGR_i^k \times TE_i^k \qquad (5)$$

The error estimation of the group-specific frontiers proposed by Huang *et al.* (2014) that is, $\hat{f}^k\left(X_i^k, \beta^k\right)$, for all $k = 1, 2, 3, \ldots. K$, the groups from the first step are expressed as:

$$ln\hat{f}^k\left(X_i^k, \beta^k\right) - lnf^k\left(X_i^k, \beta^k\right) = e_i^k - \hat{e}_i^k \qquad (6)$$

Defining the estimation error as $V_i^M = e_i^k - \hat{e}_i^k$, the meta-frontier relation can be written as:

$$ln\hat{f}^k\left(X_i^k, \beta^k\right) = lnf^M\left(X_i^k, \beta^k\right) - U_{ki}^M + V_{ki}^M, \;\; \forall_i, k = 1, 2, 3, \ldots. K \quad (7)$$

This regression resembles conventional stochastic frontier regression and is therefore called the stochastic meta-frontier (SMF) regression, in which the element of the technological gap $U_{ki}^M \geq 0$ is assumed to be a truncated half-normal distribution and independent of $V_{ki}^M$. Thus, a two-step procedure to estimate the meta-frontier can be summarized in the estimation of two stochastic frontier approach regressions:

$$lnY_i^k = f^k\left(X_i^k, \beta^k\right) + V_i^k - U_i^k, \quad i = 1, 2, 3, \ldots\ldots\ldots, N_k \qquad (8)$$

$$ln\hat{f}^k\left(X_i^k, \beta^k\right) = f^M\left(X_i^k, \beta\right) + V_i^M - U_i^M \; k = 1, 2, 3, \ldots\ldots\ldots, K \qquad (9)$$

where $\hat{f}^k\left(X_i^k, \beta^k\right)$ is the calculate of the group-specific frontier from equation (8), and regression (8) is estimated $K$ times. The estimates of output from all $K$ regions are then combined to estimate in (9). To confirm that the meta-frontier is equal to or greater than the group-specific frontiers $f^k\left(X_i^k, \beta^k\right) \leq f^M\left(X_i^k, \beta^k\right)$, the calculated TGR must be smaller than or equal to unity:

$$\widehat{TGR}_i^k = \hat{E}\left(e^{-U_{ki}^M} | \hat{\varepsilon}_{ki}^M\right) \leq 1 \qquad (10)$$

where $\hat{\varepsilon}_{ki}^M = ln\hat{f}^k\left(X_i^k, \beta^k\right) - ln\hat{f}^M\left(X_i^k, \beta\right)$ are the calculated composite residuals of (9). The technical efficiency of the i$^{th}$ farm to the meta-frontier is equal to $\widehat{MTE}_i^k = \widehat{TGR}_i^k \times \widehat{TE}_i^k$

Following similar studies in Bangladesh (e.g., Gautam and Ahmed 2019), this study adopts a parametric approach and estimates SPFs by specifying the translog stochastic frontier model for the production system k frontier (8) is as follows:

$$l\,\mathrm{n}\,Y_k^i\, ln = \beta_0^k + \sum_{j=1}^{5} \beta_j^k lnX_{ji}^k + 0.5 \sum_{j=1}^{5} \sum_{m=1}^{5} \beta_{ji}^k \left(lnX_{ji}^k\right)\left(lnX_{mi}^k\right) + \gamma D_i^k + \xi E_i^k + V_i^k - U_i^k \quad (11)$$

where the technical inefficiency model as: $U_i = \delta_0 + \sum_{j=1}^{J} \delta_j^k Z_{ij}$ (12)

where variables $Y_i$, $X_{1i}, X_{2i}, X_{3i}, X_{4i}$ and $X_{5i}$ denote rice output (kilogram), land (decimal), labor (hours), fertilizer cost (taka), other input costs (taka), and farm capital[1] (taka), respectively. Variable $D_i$ includes dummy variables for rice production season (Aman and Boro), and rice varieties such as high-yielding variety (HYV) and hybrid variety. Variable $E_i$ includes the environmental variables such as average monthly rainfall and temperature, respectively, while β, γ, and $\xi$ are unknown parameters to be estimated. In the inefficiency model, the variable $Z_{ij}$ includes the age of the household head (decision maker), education, family size, land ownership, and whether agriculture is the main source of income. The term $\delta$ is the unknown parameter to be estimated and variables $v_i$ and $u_i$ are assumed uncorrelated. To estimate unknown parameters with the stochastic production frontier and the inefficiency effect function, the maximum likelihood method is used to simultaneously.

# 3. Data and variable comparison among the climate zones

The empirical analysis utilized a dataset from the Bangladesh Integrated Household Survey in 2015 (BIHS15), which provides plot-level information on rural rice farms in Bangladesh under the direction of researchers from the International Food Policy Research Institute (IFPRI). This dataset is statistically and nationally representative of rural households in Bangladesh. The total sample size was 6,436 households in 325 primary sampling units (PSUs [i.e., villages]) from seven administrative divisions of Bangladesh, followed by two stages of stratified sampling using the sampling frame based on the population census. In the first sampling stage, the total BIHS sample of 325 PSUs/villages was allocated among the seven administrative divisions[2] based on probability proportional to size (PPS) sampling using the number of households in the population census data. Twenty households were randomly selected from each PSU/village in the second stage. Since BIHS15 survey data contains village and Upazila levels, we easily generated our data according to climate subregions (Fig. 1). After dropping plots for non-rice crops and missing information, 3,052 households cultivated 13,113 rice plots in different seasons during the 12 months from December 2013 to November 2014. We then constructed a dataset according to the seven agro-climate zones by following Sarker *et al.* (2019) to estimate regional TE differences.

The summary statistics of the variables are presented in Table 2. Interestingly, we found that the southeastern (3,315 kg/ha), northeastern (3,899 kg/ha), northern (4,877 kg/ha), northwestern (5,193 kg/ha), western (5,539 kg/ha), southwestern (4,810 kg/ha), and south-central (4,447 kg/ha) yields of rice, respectively, were high enough to show variability in rice production across the climate zones. Moreover, the western zone used the highest fertilizer and farm capital; also, it strongly depended on groundwater irrigation for rice production and had the highest dependency on agriculture. As a result, the farmers in this region are more likely to engage in farming activities that could influence the purchasing of flexible inputs and use resources more efficiently, resulting in higher yields than other regions. Contrastingly, the southeastern zone produced the lowest yield because of lower education, lower land ownership, strong dependence on rain-fed irrigation, and lower adoption of hybrid varieties. Consequently, different farm management, technology adoption, weather conditions, input

1 Farm capital is considered the total current value of farm assets at the household level.

2 The administrative structure of Bangladesh consists of divisions, districts, upazilas, and unions, in decreasing order by size. There are 7 divisions, 64 districts, 484 upazilas, and 4,498 unions (all rural).

uses, etc. create yield variations among the regions. Moreover, the northern part of the northern region's farmers did not cultivate local variety, plant in the Aus rice season, and have surface water for irrigation that could influence yield variation. On average, the northwestern zone had the highest land ownership, while less land ownership was found in the southeastern region. So, larger families have fewer opportunities to invest in rice production and may be more prone to concentrate on other income sources for their livelihood; hence, the farmers with larger family sizes in the northeastern zone of Bangladesh produce lower yields. Finally, the highest rainfall but the lowest temperature is found in the northeastern region, while the lowest rainfall and temperature are found in the southwestern region, which could cause yield variation.

**Table 2.** Variations in output, the input used, and relevant variables by climatic zones

| Variable | Southeastern | Northeastern | Northern part northern | Northwestern | Western | Southwestern | Southcentral | All areas |
|---|---|---|---|---|---|---|---|---|
| Output (kg/plot) | 451 (471) | 820 (1138) | 550 (526) | 486 (534) | 611 (721) | 491 (545) | 530 (613) | 534 (629) |
| Yield (kg/ha) | 3315 (1538) | 3899 (1452) | 4877 (1655) | 5193 (1767) | 5539 (1770) | 4810 (1772) | 4447 (1903) | 4612 (1873) |
| Land (ha) | 0.145 (0.152) | 0.206 (0.255) | 0.115 (0.106) | 0.092 (0.089) | 0.112 (0.123) | 0.104 (0.115) | 0.118 (0.112) | 0.119 (0.123) |
| Labor (hours/ha) | 670.7 (680.1) | 615.8 (264.8) | 840.0 (374.5) | 942.1 (474.4) | 914.6 (622.7) | 1025.5 (796.4) | 893.7 (510.5) | 888.0 (588.7) |
| Fertilizer (USD/ha) | 74.00 (62.20) | 64.43 (64.07) | 133.71 (75.37) | 150.15 (85.45) | 150.52 (165.3) | 147.01 (116.0) | 99.93 (73.72) | 117.7 (99.3) |
| Other costs (USD/ha) | 197.84 (120.61) | 198.08 (98.16) | 214.38 (108.9) | 256.4 (124.0) | 250.7 (141.7) | 237.62 (135.0) | 251.94 (139.7) | 240.1 (133.4) |
| Farm asset (USD/ha) | 948.77 (2809.3) | 583.3 (1227.3) | 1915.4 (6909.3) | 1729.0 (5537.3) | 3602.2 (10428) | 1604.8 (4552) | 1779.9 (12548) | 1793.4 (9201.9) |
| Aus rice | 0.223 (0.416) | 0.149 (0.356) | --- | 0.041 (0.198) | 0.018 (0.133) | 0.020 (0.140) | 0.034 (0.180) | 0.052 (0.221) |
| Aman rice | 0.648 (0.478) | 0.374 (0.484) | 0.602 (0.490) | 0.534 (0.499) | 0.503 (0.500) | 0.620 (0.485) | 0.421 (0.494) | 0.508 (0.500) |
| Boro rice | 0.129 (0.335) | 0.477 (0.500) | 0.398 (0.490) | 0.425 (0.495) | 0.479 (0.500) | 0.360 (0.480) | 0.546 (0.498) | 0.441 (0.497) |
| Local variety | 0.402 (0.490) | 0.040 (0.196) | --- | 0.010 (0.099) | 0.028 (0.166) | 0.083 (0.276) | 0.133 (0.340) | 0.109 (0.312) |
| HYV | 0.566 (0.496) | 0.891 (0.312) | 0.867 (0.340) | 0.879 (0.326) | 0.868 (0.338) | 0.864 (0.343) | 0.777 (0.416) | 0.807 (0.395) |
| Hybrid | 0.032 (0.177) | 0.069 (0.254) | 0.133 (0.340) | 0.111 (0.315) | 0.104 (0.305) | 0.053 (0.225) | 0.089 (0.285) | 0.084 (0.277) |
| Rain fed | 0.766 (0.423) | 0.524 (0.500) | 0.306 (0.461) | 0.187 (0.390) | 0.064 (0.245) | 0.282 (0.450) | 0.363 (0.481) | 0.337 (0.473) |
| Ground water | 0.066 (0.248) | 0.088 (0.284) | 0.694 (0.461) | 0.711 (0.454) | 0.918 (0.275) | 0.670 (0.470) | 0.449 (0.497) | 0.531 (0.499) |
| Surface water | 0.168 (0.374) | 0.387 (0.488) | --- | 0.102 (0.303) | 0.018 (0.133) | 0.048 (0.213) | 0.188 (0.391) | 0.132 (0.338) |
| Clay | 0.039 (0.194) | 0.032 (0.177) | 0.004 (0.062) | 0.025 (0.156) | 0.001 (0.028) | 0.041 (0.197) | 0.024 (0.153) | 0.025 (0.156) |
| Loam | 0.032 (0.177) | 0.252 (0.434) | 0.248 (0.432) | 0.250 (0.433) | 0.126 (0.332) | 0.189 (0.391) | 0.170 (0.376) | 0.176 (0.381) |
| Sandy | 0.119 (0.323) | 0.047 (0.212) | 0.087 (0.282) | 0.080 (0.271) | 0.024 (0.154) | 0.054 (0.226) | 0.056 (0.229) | 0.063 (0.242) |
| Clay loam | 0.625 (0.484) | 0.507 (0.500) | 0.372 (0.484) | 0.404 (0.491) | 0.605 (0.489) | 0.474 (0.499) | 0.516 (0.500) | 0.503 (0.500) |
| Sandy loam | 0.184 (0.388) | 0.162 (0.369) | 0.290 (0.454) | 0.242 (0.428) | 0.244 (0.430) | 0.243 (0.429) | 0.235 (0.424) | 0.233 (0.423) |
| Head age | 49.80 (12.56) | 49.92 (13.21) | 45.52 (13.16) | 48.26 (12.15) | 46.83 (12.32) | 48.18 (12.40) | 48.65 (12.60) | 48.31 (12.59) |
| Head education | 3.283 (3.810) | 3.860 (3.742) | 3.311 (3.632) | 4.387 (4.254) | 3.915 (4.305) | 4.101 (4.209) | 3.428 (3.925) | 3.720 (4.039) |
| Own land | 0.427 (0.495) | 0.677 (0.468) | 0.700 (0.458) | 0.838 (0.369) | 0.584 (0.493) | 0.670 (0.470) | 0.534 (0.499) | 0.612 (0.487) |
| Family size | 4.741 (1.823) | 6.122 (2.241) | 4.305 (1.673) | 4.312 (1.502) | 4.351 (1.467) | 4.529 (1.730) | 4.766 (1.869) | 4.906 (1.981) |
| Income source (Agril. = 1) | 0.572 (0.495) | 0.646 (0.479) | 0.468 (0.499) | 0.559 (0.497) | 0.685 (0.465) | 0.605 (0.489) | 0.621 (0.485) | 0.604 (0.489) |
| Negative shocks (0/1) | 0.409 (0.492) | 0.205 (0.404) | 0.306 (0.461) | 0.343 (0.475) | 0.663 (0.473) | 0.353 (0.478) | 0.425 (0.494) | 0.405 (0.491) |
| Migration (0/1) | 0.357 (0.479) | 0.285 (0.452) | 0.272 (0.445) | 0.148 (0.355) | 0.273 (0.446) | 0.145 (0.352) | 0.306 (0.461) | 0.255 (0.436) |
| Market distance (km) | 4.056 (5.063) | 5.07 (5.586) | 4.65 (3.37) | 4.46 (6.44) | 4.96 (3.77) | 4.45 (4.37) | 4.52 (6.09) | 4.54 (5.43) |
| Average monthly rainfall | 156.84(14.16) | 235.06 (53.90) | 162.33 (12.30) | 133.31 (16.93) | 122.15(9.05) | 144.06 (5.601) | 163.16 (32.46) | 149.65 (37.76) |
| Average temperature | 25.33 (0.199) | 23.89 (1.06) | 24.69 (0.208) | 25.35 (0.336) | 25.51 (0.180) | 25.83 (0.280) | 25.05 (0.464) | 25.21 (0.610) |
| Observations | 1172 | 660 | 790 | 1735 | 1275 | 2291 | 5190 | 13113 |

Note: Standard deviations are in parentheses. All costs are measured at Bangladesh taka, which is approximately equal to $ 0.012.

# 4. Empirical results and discussion

## 4.1 Parameter estimates of the SPF model

The maximum likelihood estimates (MLE) of the translog stochastic frontier parameters, pooled, and meta-frontiers are reported in Table 3. The values of the explanatory variables $X_{ji}$ ($j = 1,2,3, \dots ,5$), are divided by their respective means. Therefore, the coefficients $\beta_j$ of $\ln X_{ji}$ ($j = 1,2,3, \dots ,5$) can be interpreted as the elasticities of output of the corresponding inputs evaluated at their means. The size of the output elasticities differed among the climate zones. All first-order estimated coefficients have values from zero to one in the pooled dataset, indicating that the monotonicity conditions are satisfied. The return to scale shows that the different structures of production among the climate zones and all of the rest are operating under increasing returns to scale, except for the northeastern area. The gamma parameters ($\gamma = \sigma_u^2/(\sigma_u^2 + \sigma_v^2)$ measure the extent to which the variation in the composite error term is attributed to the inefficiency component ($\sigma_u^2$) as a proportion of the combined error ($\sigma_u^2 + \sigma_v^2$). The translog function (Table 3) produced different gamma values. For example, there was 0.83 for the southeastern area and 0.94 for the northeastern area, indicating the percentage variation in frontier output as a result of the presence of inefficiency effects (group-specific variable). This indicates that external factors stimulates rice production in Bangladesh.

The contribution of land area is the highest concerning rice production in Bangladesh, with the elasticity of output ranging from 0.603 to 0.924 among climate zones, including the meta-frontier model. Notably, labor is the most crucial contributor, and the elasticity of labor is positively significant in all climate regions except the northwestern and southwestern zones, implying that a marginal increase in the hours of employed farm labor will increase rice output. The elasticity of fertilizer was found to be a positive and significant contributor in all climate zones. However, fertilizer and other variable costs in the southeastern zone show the highest contribution among the climate zones. The elasticity of farm assets in the northern part of the northern region was found to be negative and significant, suggesting that farmers should be careful when selecting farm capital to invest in because rice output reduces excess investment in farm capitals. These estimates are compatible with those of other studies on Bangladeshi rice farmers (Asadullah and Rahman 2009; Gautam and Ahmed 2019). In the case of the meta-frontier model, the coefficients for all the primary variables were positive and statistically significant, suggesting that all key inputs positively influenced rice production, which is consistent with Asante *et al.* (2019.

The coefficient of HYV, hybrid variety, and the Boro rice season was positive and statistically significant in all climate zones except the northern part of the northern zone. These results revealed that the HYV, hybrid variety, and Boro rice season shifted the production frontier upwards, leading to higher rice productivity in all climate zones. Specifically, rice production in the western zone mostly depends on groundwater irrigation (see Table 2), and it is produced during the dry winter season with little rainfall. In this case, we naturally found no difference between rain-fed and surface or groundwater as water sources; also, the negative effect of surface water use shows its disadvantage against groundwater use. Subsequently, rice production in the southeastern zone is grown mainly depending on rainfall and is produced in the rainy season with abundant rainfall. In this case, we naturally expect no advantage of ground or surface water against rain-fed farming, and the negative effect of surface water use shows its disadvantage against groundwater use. We found that average monthly rainfall had a significantly negative impact on rice production in all climate zones. This is because unnecessary and excessive rainfall at an appropriate time creates a barrier to rice production. Conversely, the monthly average temperature significant and positively affected rice production in all climate zones, except in the northeastern and western zones.

## 4.2 Factors affecting TE in rice production across climatic zones

The MLE of the factors influencing TE in rice production among the climate zones are presented in Table 3. The determinants of TE vary across climate zones. In the pooled model, except for household head education, all parameters were statistically significant. In the context of Bangladesh, household head is the decision-maker who has the final say and better knows about new technology than other family members. The significant and positive sign of household head age shows that older farmers tend to be more inefficient, indicating that younger farmers pay more attention to rice production, which is in line with Mariano *et al.* (2011). We found that the education coefficient was positively and significantly associated with the inefficiency in the western and southern central zones, revealing that educated farmers have little engagement in farming practices as they have different alternative sources of income. However, higher education levels increase TE in the northern part of the northern, northwestern, and southwestern zones. Generally, northeastern, western, and south-central farmers pay more attention to their own land farm practices than sharecropping, but farmers in the northern part of the northern region give more attention to sharecropping than their own farming. This indicates that sharecroppers are more efficient than owner-operators because of their eagerness to maximize their return on investment, which is consistent with Anik and Salam (2017). The number of household members was also negatively associated with TE in the southeastern zone, suggesting that probably reflecting underemployment of family members is consistent with Mariano *et al.* (2011). Depending on farm activity alone as a primary source of income increases TE in all climate zones except the southwestern one, indicating that farmers pay more attention to adopting and applying modern technology in production practices. When a farmer faces negative shocks, his/her efficiency decreases. Barrett et al. (2006) reported that the negative shocks can divert a farmer's managerial attention, which in effect reduces farm production, causing transitory decreases in efficiency, and consequently, the farmer produces below the potential level of output. The findings for western and southwestern regions indicate a significant adverse effect of migration on farming efficiency, indicating that households with better educated family worker, suggesting the presence of labor market imperfections with farm households relying also exclusively on family labor, which inline with Sauer et al. (2015). The negative and significant coefficient of migration for southeastern region, meaning that migration leads to a reduction in farming inefficiency because income generated from migration allows farmers to purchase better inputs while working within own counties still allows them to be able to take care of own farm work especially during the most critical production seasons. This result is consistent with Yang et al. (2016). Long market distance influences to increase technical inefficiency due to long distances could be barriers to timely purchasing inputs. Subsequently, southwestern farmers seek out other non-farm jobs and businesses outside of rice production.

**Table 3.** MLE for first-order parameters of the translog production frontier by climatic zone

| | South-eastern | North-eastern | Northern part northern | North-western | Western | South-western | South central | All zones | Meta-frontiers |
|---|---|---|---|---|---|---|---|---|---|
| Constant | 4.634*** | 9.256*** | -3.550 | 5.286* | 98.467*** | 4.121*** | 6.130*** | 7.455*** | 6.708*** |
| | (1.716) | (1.371) | (2.820) | (3.079) | (19.682) | (1.601) | (0.543) | (0.332) | (0.092) |
| Land ($x_1$) | 0.599*** | 0.642*** | 0.788*** | 0.889*** | 0.918*** | 0.922*** | 0.842*** | 0.861*** | 0.854*** |
| | (0.055) | (0.078) | (0.055) | (0.035) | (0.031) | (0.023) | (0.019) | (0.011) | (0.003) |
| Labor ($x_2$) | 0.152*** | 0.173*** | 0.149*** | -0.029 | 0.033 | 0.005 | 0.032* | 0.019** | 0.030*** |
| | (0.042) | (0.057) | (0.041) | (0.028) | (0.027) | (0.018) | (0.017) | (0.009) | (0.003) |
| Fertilizer ($x_3$) | 0.114*** | 0.044** | 0.061* | 0.099*** | 0.023 | 0.035*** | 0.081*** | 0.081*** | 0.072*** |
| | (0.025) | (0.023) | (0.036) | (0.020) | (0.021) | (0.013) | (0.009) | (0.006) | (0.002) |
| Other cost($x_4$) | 0.195*** | 0.082** | 0.034 | 0.049** | 0.059** | 0.043** | 0.035*** | 0.041*** | 0.051*** |
| | (0.047) | (0.053) | (0.041) | (0.025) | (0.024) | (0.018) | (0.014) | (0.008) | (0.002) |
| Farm asset ($x_5$) | 0.014 | 0.033*** | -0.031*** | 0.011* | 0.002 | 0.023*** | 0.017*** | 0.011*** | 0.013*** |
| | (0.011) | (0.012) | (0.009) | (0.007) | (0.006) | (0.007) | (0.004) | (0.002) | (0.001) |
| ($x_1x_1$) | -0.207*** | 0.138* | -0.192*** | 0.083** | -0.097*** | -0.027 | -0.043*** | -0.072*** | -0.065*** |
| | (0.040) | (0.082) | (0.070) | (0.039) | (0.031) | (0.021) | (0.013) | (0.009) | (0.003) |
| ($x_1x_2$) | 0.212*** | -0.219** | 0.215** | -0.282*** | 0.074 | 0.029 | 0.094*** | 0.097*** | 0.088*** |
| | (0.049) | (0.101) | (0.098) | (0.057) | (0.050) | (0.028) | (0.024) | (0.014) | (0.004) |
| ($x_1x_3$) | -0.018 | -0.020 | 0.102 | 0.091*** | 0.047* | 0.001 | 0.027*** | 0.018*** | 0.021*** |
| | (0.019) | (0.031) | (0.068) | (0.027) | (0.028) | (0.011) | (0.007) | (0.005) | (0.001) |
| ($x_1x_4$) | 0.115** | 0.002 | 0.095 | -0.038 | 0.071* | 0.028 | -0.023 | 0.034*** | 0.018*** |
| | (0.052) | (0.107) | (0.085) | (0.055) | (0.051) | (0.026) | (0.020) | (0.013) | (0.004) |
| ($x_1x_5$) | -0.016 | -0.028* | 0.033 | 0.027* | 0.005 | 0.030*** | 0.0001 | 0.007** | 0.009*** |
| | (0.012) | (0.016) | (0.022) | (0.014) | (0.010) | (0.007) | (0.005) | (0.003) | (0.001) |
| ($x_2x_2$) | -0.068*** | 0.047 | -0.120*** | 0.093*** | -0.084*** | -0.024* | -0.033** | -0.037*** | -0.032*** |
| | (0.016) | (0.048) | (0.046) | (0.028) | (0.022) | (0.014) | (0.016) | (0.007) | (0.002) |
| ($x_2x_3$) | -0.019 | -0.071*** | 0.044 | -0.040 | 0.100** | -0.018** | -0.009 | -0.026*** | -0.024*** |
| | (0.016) | (0.027) | (0.063) | (0.032) | (0.044) | (0.009) | (0.007) | (0.004) | (0.001) |
| ($x_2x_4$) | -0.073* | 0.166** | 0.039 | 0.151*** | -0.019 | 0.048** | -0.027 | 0.006 | 0.010*** |
| | (0.044) | (0.082) | (0.088) | (0.043) | (0.042) | (0.024) | (0.022) | (0.013) | (0.004) |
| ($x_2x_5$) | 0.010 | 0.022 | 0.018 | -0.002 | -0.002 | -0.022*** | -0.007 | -0.008*** | -0.008*** |
| | (0.011) | (0.014) | (0.018) | (0.014) | (0.013) | (0.006) | (0.005) | (0.003) | (0.001) |
| ($x_3x_3$) | 0.011*** | 0.003 | -0.068** | 0.022*** | 0.003 | 0.007*** | 0.009*** | 0.011*** | 0.010*** |

| | South-eastern | North-eastern | Northern part northern | North-western | Western | South-western | South central | All zones | Meta-frontiers |
|---|---|---|---|---|---|---|---|---|---|
| | (0.004) | (0.005) | (0.029) | (0.005) | (0.011) | (0.002) | (0.001) | (0.001) | (0.0002) |
| $(x_3x_4)$ | 0.018 | 0.083*** | -0.070 | -0.089*** | -0.141*** | -0.004 | -0.035*** | -0.021*** | -0.022*** |
| | (0.014) | (0.032) | (0.067) | (0.022) | (0.031) | (0.012) | (0.007) | (0.004) | (0.001) |
| $(x_3x_5)$ | 0.008* | -0.010* | -0.007 | -0.004 | 0.006 | -0.004 | 0.002 | -0.001 | -0.0003 |
| | (0.005) | (0.006) | (0.015) | (0.009) | (0.007) | (0.003) | (0.001) | (0.001) | (0.0003) |
| $(x_4x_4)$ | 0.010 | -0.112*** | -0.037 | 0.008 | 0.036 | -0.032*** | 0.040*** | -0.008 | -0.002 |
| | (0.033) | (0.043) | (0.042) | (0.025) | (0.027) | (0.013) | (0.011) | (0.007) | (0.002) |
| $(x_4x_5)$ | 0.018* | 0.001 | -0.035** | -0.013 | 0.004 | -0.007 | 0.004 | 0.004 | 0.003*** |
| | (0.011) | (0.012) | (0.017) | (0.011) | (0.010) | (0.006) | (0.004) | (0.003) | (0.001) |
| $(x_5x_5)$ | -0.001 | 0.002 | -0.004** | 0.002 | -0.001 | 0.003** | 0.002*** | 0.001 | 0.001*** |
| | (0.002) | (0.002) | (0.002) | (0.001) | (0.001) | (0.001) | (0.001) | (0.0001) | (0.0001) |
| HYV | 0.319*** | 0.323*** | --- | 0.463*** | 0.529*** | 0.405*** | 0.343*** | 0.363*** | 0.361*** |
| | (0.028) | (0.082) | | (0.068) | (0.050) | (0.033) | (0.017) | (0.011) | (0.003) |
| Hybrid | 0.499*** | 0.543*** | 0.097*** | 0.633*** | 0.739*** | 0.475*** | 0.450*** | 0.519*** | 0.512*** |
| | (0.075) | (0.098) | (0.031) | (0.070) | (0.055) | (0.043) | (0.022) | (0.015) | (0.004) |
| Aman rice | -0.150*** | 0.113*** | --- | 0.036 | -0.109** | 0.155*** | -0.002 | -0.044*** | -0.047*** |
| | (0.030) | (0.036) | | (0.035) | (0.049) | (0.046) | (0.024) | (0.013) | (0.004) |
| Boro rice | 0.013 | 0.232*** | 0.211*** | 0.312*** | 0.157*** | 0.412*** | 0.397*** | 0.253*** | 0.253*** |
| | (0.058) | (0.065) | (0.031) | (0.038) | (0.051) | (0.048) | (0.026) | (0.014) | (0.004) |
| Ground water | -0.088 | 0.117 | -0.040 | 0.037* | -0.036 | -0.004 | -0.019 | 0.023*** | 0.013*** |
| | (0.070) | (0.073) | (0.030) | (0.021) | (0.032) | (0.019) | (0.015) | (0.008) | (0.002) |
| Surface water | -0.010 | 0.091 | --- | -0.115*** | -0.115* | 0.020 | -0.020 | -0.011 | -0.006*** |
| | (0.037) | (0.060) | | (0.031) | (0.063) | (0.034) | (0.017) | (0.010) | (0.003) |
| Clay | 0.056 | 0.109 | -0.147 | -0.006 | 0.029 | 0.079* | 0.052* | 0.062*** | 0.067*** |
| | (0.070) | (0.086) | (0.158) | (0.046) | (0.223) | (0.044) | (0.032) | (0.020) | (0.006) |
| Loam | 0.096 | 0.217*** | 0.049 | 0.115*** | -0.047 | 0.079** | 0.003 | 0.031** | 0.028*** |
| | (0.067) | (0.063) | (0.050) | (0.029) | (0.053) | (0.031) | (0.020) | (0.013) | (0.003) |
| Clay loam | -0.041 | 0.151** | -0.009 | 0.131*** | -0.073 | 0.052* | -0.012 | 0.016 | 0.015*** |
| | (0.035) | (0.063) | (0.049) | (0.026) | (0.049) | (0.029) | (0.019) | (0.012) | (0.003) |
| Sandy loam | -0.043 | 0.234*** | 0.014 | 0.167*** | -0.074 | 0.064** | -0.037* | 0.027** | 0.020*** |
| | (0.039) | (0.066) | (0.048) | (0.028) | (0.051) | (0.031) | (0.020) | (0.012) | (0.003) |

| | South-eastern | North-eastern | Northern part northern | North-western | Western | South-western | South central | All zones | Meta-frontiers |
|---|---|---|---|---|---|---|---|---|---|
| Monthly rainfall | -0.187 | -0.341** | 0.384* | -0.134 | -5.898*** | -0.134 | -0.140*** | -0.244*** | -0.185*** |
| | (0.157) | (0.143) | (0.216) | (0.215) | (1.291) | (0.186) | (0.038) | (0.025) | (0.007) |
| Average temperature | 0.109* | -0.063** | 0.328*** | 0.049 | -2.502*** | 0.097*** | 0.027* | -0.002 | 0.017*** |
| | (0.059) | (0.026) | (0.080) | (0.082) | (0.529) | (0.035) | (0.015) | (0.009) | (0.002) |
| ***Technical inefficiency effects models*** | | | | | | | | | |
| Constant | -1.708*** | -1.657*** | -2.503*** | -1.733*** | -3.936*** | -1.810*** | -1.336*** | -1.700*** | |
| | (0.341) | (0.469) | (0.583) | (0.286) | (0.298) | (0.216) | (0.155) | (0.090) | |
| Land | -0.052 | 0.030 | 0.207 | -0.122** | 0.348*** | 0.126** | -0.145*** | -0.007 | |
| | (0.073) | (0.090) | (0.140) | (0.065) | (0.057) | (0.052) | (0.034) | (0.020) | |
| Head age | 0.014*** | 0.012*** | -0.012** | 0.003 | 0.007* | -0.005 | 0.006*** | 0.004*** | |
| | (0.004) | (0.005) | (0.006) | (0.004) | (0.004) | (0.003) | (0.002) | (0.001) | |
| Head education | -0.009 | 0.003 | -0.080*** | -0.032*** | 0.058*** | -0.027*** | 0.009* | -0.002 | |
| | (0.014) ) | (0.017) | (0.022) | (0.010) | (0.012) | (0.008) | (0.005) | (0.003) | |
| Own land (D) | -0.004 | -0.590*** | 0.955*** | -0.003 | -0.251*** | 0.170** | -0.087* | -0.077*** | |
| | (0.106) | (0.148) | (0.199) | (0.115) | (0.099) | (0.077) | (0.047) | (0.029) | |
| Family size | 0.049* | 0.073** | -0.124*** | 0.024 | 0.113*** | -0.034** | 0.024** | 0.030*** | |
| | (0.027) | (0.031) | (0.044) | (0.025) | (0.033) | (0.018) | (0.010) | (0.007) | |
| Main income | -0.375*** | -0.627*** | -0.620*** | -0.115 | -0.296*** | 0.272*** | -0.033 | -0.028 | |
| (agriculture = 1) | (0.111) | (0.141) | (0.172) | (0.084) | (0.109) | (0.078) | (0.047) | (0.029) | |
| Negative shocks | 0.091 | 0.134 | 0.827*** | 0.085 | 1.067*** | 0.320*** | 0.339*** | 0.317*** | |
| | (0.099) | (0.159) | (0.169) | (0.087) | (0.103) | (0.073) | (0.044) | (0.028) | |
| Migration | -0.020** | 0.015 | -0.005 | 0.002 | 0.075*** | 0.048*** | 0.006 | 0.021*** | |
| | (0.009) | (0.013) | (0.016) | (0.011) | (0.009) | (009) | (0.005) | (0.003) | |
| Market distance (km) | 0.012 | -0.037*** | 0.096*** | 0.032*** | -0.052*** | 0.007 | -0.013*** | -0.003 | |
| | (0.010) | (0.012) | (0.023) | (0.008) | (0.011) | (0.008) | (004) | (0.003) | |
| ***Variance and other model statistics*** | | | | | | | | | |
| Sigma square | 0.2181 | 0.2021 | 0.1167 | 0.1998 | 0.0306 | 0.1904 | 0.2850 | 0.2073 | 0.0100 |
| Gamma | 0.8312*** | 0.9433*** | 0.7015*** | 0.8847*** | 0.6391*** | 0.8589*** | 0.9223*** | 0.8811*** | 0.4675*** |
| Log likelihood | -511.08 | -134.65 | -129.55 | -205.21 | -198.23 | -646.46 | -1621.30 | -4397.84 | 13849.6 |
| Returns to scale | 1.074*** | 0.9738*** | 1.002*** | 1.018*** | 1.033*** | 1.028*** | 1.008*** | 1.013*** | 1.019 |

Notes: "***", "**" and "*" indicate significance at the 1%, 5% and 10% level. Standard errors are in parentheses..

## 4.4 TE, meta-frontier technical efficiency and technology gap ratio

The group technical efficiency ($TE_G$), TGR, and MTE are presented in Table 4. First, we compared the variation in TE across the seven climate zones. The average TE in the pooled dataset shows that farmers produce only 69.87% of the maximum achievable output for a given level of inputs, suggesting that if farms operate at the most efficient production level, they could achieve significant TE gains. These achievements could be expressed as the use of input savings or higher production with positive impacts on the sector's productivity. The TGR and MTE indicate significant scope for improving the sector's performance. Among the climate zones, the farmers in the northwestern zone had the highest (77.8%), while southeastern farmers had the lowest (67.6%) efficiency. This shows that the northwestern and southwestern regions have the potential to increase rice output by 22.2% and 32.4%, respectively, in the short run by adopting good agronomic practices and improved technologies. Piya et al. (2012) and Narala & Zala (2010) argued more than 27% rice production can be increased with the available technology while Tijani (2006) revealed 13% rice output short of the highest possible level due to inefficiency. The highest mean meta-frontier TE is obtained by farmers in the northwestern region (66.3%) and the lowest in the southeastern region (51.5%), indicating that farmers in the northwestern region are more technically efficient compared to the other climate zones. Southeastern farmers could adopt modern rice production practices to catch up with the northern part of the northern zone. The difference in the results is expected because it is hypothesized that farmers in various climate zones would perform differently because of the various production environments and face various issues or challenges in which farmers operate within these climate zones.

**Table 4.** Technical efficiencies and TGR by climate zone

| | | Mean | SD | Minimum | Maximum |
|---|---|---|---|---|---|
| Southeastern | $TE_G$ | 0.6759 | 0.1708 | 0.1055 | 0.9496 |
| | TGR | 0.7155 | 0.1841 | 0.1117 | 1.0000 |
| | MTE | 0.5146 | 0.2260 | 0.0118 | 1.0000 |
| Northeastern | $TE_G$ | 0.7060 | 0.1821 | 0.1313 | 0.9614 |
| | TGR | 0.7454 | 0.1940 | 0.1394 | 1.0000 |
| | MTE | 0.5612 | 0.2451 | 0.0183 | 1.0000 |
| Northern part northern | $TE_G$ | 0.7557 | 0.1347 | 0.0660 | 0.9642 |
| | TGR | 0.8002 | 0.1433 | 0.0760 | 1.0000 |
| | MTE | 0.6238 | 0.1950 | 0.0050 | 1.0000 |
| Northwestern | $TE_G$ | 0.7775 | 0.1294 | 0.0408 | 0.9506 |
| | TGR | 0.8298 | 0.1425 | 0.0438 | 1.0000 |
| | MTE | 0.6632 | 0.1828 | 0.0018 | 1.0000 |
| Western | $TE_G$ | 0.7530 | 0.1718 | 0.0155 | 0.9788 |
| | TGR | 0.7880 | 0.1805 | 0.0158 | 1.0000 |
| | MTE | 0.6243 | 0.2126 | 0.0002 | 1.0000 |
| Southwestern | $TE_G$ | 0.7143 | 0.1571 | 0.0828 | 0.9605 |
| | TGR | 0.7521 | 0.1658 | 0.0869 | 1.0000 |
| | MTE | 0.5632 | 0.2113 | 0.0072 | 0.9885 |
| South central | $TE_G$ | 0.7017 | 0.1660 | 0.0399 | 0.9642 |
| | TGR | 0.7411 | 0.1752 | 0.0413 | 1.0000 |
| | MTE | 0.5491 | 0.2201 | 0.0016 | 1.0000 |
| All areas | $TE_G$ | 0.6987 | 0.1652 | 0.0216 | 0.9655 |
| | TGR | 0.7369 | 0.1716 | 0.0222 | 1.0000 |
| | MTE | 0.5431 | 0.2151 | 0.0006 | 0.9826 |

The variations of estimated TGRs range from 0.72 to 0.83 and are varies from each other (F-stat of 69.49 with a p-value of 0.000), signifying that technology gaps are apparent in rice production across the climate zones. Given the available factors, the northwestern farmers are closer to the meta-frontier, indicating a smaller technology gap, and are probable to produce nearer to their highest potential output than those of other climate zones. This result is consistent with those of Danso-Abbeam and Baiyegunhi (2020). However, the maximum TGR in all climate zones is equal to one, indicating that at least one farmer operates on the meta-frontier, suggesting that it is possible to close the technology gap by appropriately adopting the available technology. The highest TGR in the northwestern region shows that farmers have efficiently executed crop management practices to mitigate the unfavorable environment's productivity-reducing effects. This zone may be recognized for its unique environmental characteristics, such as relatively moderate rainfall, which tends to improve soil health and is more likely to adopt technology, explaining their more remarkable performance in rice production. Therefore, favorable environmental conditions might have contributed to the productivity gains from improved technology.

The causes of the highest mean TE, TGR, and MTE were found in the northwestern zone because the highest education level, lower migration and land ownership (Table 1) can play a vital role in increasing rice productivity, boosting potential output, and improving TE. This finding is consistent with Asadullah and Rahman (2009), who argued that education significantly contributes to productivity and TE. Rahman (2003) observed owner-operators work with a relatively higher level of efficiency than tenants. Subsequently, the farmers in the southeastern zone mostly depend on rainfall, lower adoption of the hybrid variety, and lower land ownership, which could negatively affect rice production and produce lower efficiency.

# 5. Conclusion and implications

In this study, we compared the technical efficiency (TE) and technological gap ratios (TGRs) of rice production among the seven climate sub-zones in Bangladesh using a stochastic meta-frontier approach, where there is heterogeneous technology adoption among farmers and environmental variations by using a nationally representative household-level dataset. Empirical results revealed that the estimated output elasticities of all inputs were significant and varied across the climate zones. Farm-specific variables such as household head age, education, land ownership, family size, negative shocks, migration and main income source have different effects on TE. The estimated mean TE score ranges from 0.676 to 0.778, suggesting that rice farms across climate zones use different technologies for rice production, and the estimated TGR ranges from 0.716 to 0.830, indicating that the technological gap varies across the climate zones. The northwestern farmers have higher mean TE and less distance from the meta-frontier than other climate zones, suggesting that all the climate zone farmers, except the northwestern ones, should improve their production. Notably, farmers in the southeastern zone have lower adoption technology and adapt their management practices according to the climate constraints they face. Such findings also suggest that the government should emphasize technology development and provision region-specific technologies, such as introducing salinity, cold, and drought-tolerant rice varieties.

Technical efficiency could be improved across the climate zones by advancing the production frontier and improving technology diffusion within the region. Furthermore, across the climate zones, some farmers unable to achieve the maximum possible output for the meta-frontier. This implies that there is possibility for farmers to increase their rice productivity through the adoption and diffusion of modern rice production technologies, such as improved seeds, fertilizer use, and climate-sensitive rice varieties. The study revealed that better education, exclusive farm activity as a primary source of income, and increased land ownership would help improve TE levels and technology in Bangladesh.

So, the government of Bangladesh can emphasize more investment in research to develop advanced climate zone-specific technology and provide input subsidies that have been found to increase rice productivity. Additionally, increasing rice productivity in Bangladesh will require policies that improve farmers' access to extension services to encourage the adoption of climate zone-specific technologies and appropriate crop management practices. Subsequently, public and private organizations should come forward to make investments in agricultural technology acquisition and promote technological innovation by supporting research and development efforts to reduce technological gaps. More specifically, the southeastern region needs to install advanced production technologies to catch up to the northwestern region.

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