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Technical and environmental efficiency of agriculture sector in South Asia: a stochastic frontier analysis approach

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Abstract
The purpose of this study was to measure and assess comparative study of technical and environmental efficiency of agriculture sector in South Asia using balanced panel data for the period 2002–2016. The translog stochastic frontier analysis approach was applied to estimate output-oriented technical efficiency and input-oriented environmental efficiency. Results of translog production model give that output elasticity w.r.t. land, labor, capital and fertilizer is 2.13, 1.26, 0.01 and 0.17, respectively. Log likelihood test shows that there is technical inefficiency in the agriculture sector of South Asian countries. The average value of output-oriented technical efficiency for South Asian countries was 0.92 ranging from 0.82 to 0.97. This suggests that agricultural production of South Asian region could be increased up to 8 percent by eliminating the effects of technical inefficiency. Moreover, the findings show that Sri Lanka is the most technically efficient country having efficiency 0.99 followed by India (0.98), Bhutan (0.93), Bangladesh (0.89), Nepal (0.88) and Pakistan (0.85). The results of input-oriented environmental efficiency score of South Asia were 0.77 ranging from 0.57 to 0.97. This shows that there is opportunity to enhance environmental efficiency of South Asian countries by 23%. Sri Lanka achieved the highest environmental efficiency (0.97) followed by India (0.96), Bhutan (0.72), Bangladesh (0.71), Pakistan (0.67) and Nepal (0.57). It is recommended that there must be collaboration among the South Asian countries in research and development especially in agriculture sector on priority bases.

Keywords Efficiency · Agriculture · Stochastic frontier analysis · Pakistan

1 Introduction

Utilization of fertilizer is a key factor of grain yields. As globally indicated by the Food and Agriculture Organization (FAO), the fertilizer adds 40–60% increase to the agriculture output. South Asian countries are using 150 kg per hectare excessive fertilizer for agriculture sector that will cause depletion of natural resources and cause adverse impacts on environment too (FAO 2018). South Asian countries include Afghanistan,

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Bangladesh, Bhutan, India, Maldives, Nepal, Pakistan and Sri Lanka, with a territory of 5.2 million square kilometers that is about 1% of the total world populace. South Asia is the most densely populated region in the world. South Asia is the home of about 1.8 billion people that is approximately 25% of the total populace. About 57% of South Asia has an agricultural land, and about 60% population of South Asia is involved in agriculture sector. It provides livelihood to a large portion of the population and employs more than 40% of the workforce. It is also an important driver for growth and poverty alleviation in this region. Agriculture sector is playing and continues to play an essential role in the economy of South Asian Countries. It is also an important driver for growth and poverty alleviation in this region. So, this region rightly pins its expectation on agriculture sector. The growing population causes the rise of demand for food which is stressing the agriculture sector, as it battles to meet the current and future food demand. The matter becomes serious as the regions use inefficient inputs such as fertilizer. Agriculture sector, as a sector is principally interrelated with the environment, has significant potential to produce environmentally detrimental by-products. Overall agriculture sector plays a significant part in economic development in Asia (FAO 2016). The main aim of policy makers has always been the sustainability of agriculture sector by considering the impacts on the environment during production (Kuo et al. 2014). Increasing yield while minimizing environmental pollution in agricultural production is nowadays the primary concern in agriculture-based countries (Vu et al. 2019). Increasing agricultural productivity is important in the South Asia to meet the growing demand for food. Increasing agricultural productivity has been accompanied by higher fertilizer use, causing environmental degradation.

However, the present emphasis on environmental issues has led the farmers to target improvements in both agricultural productivity and environmental performance. One of the challenges of sustainable agriculture centers on using fertilizer efficiently to grow crops without polluting the environment. In addition, unsustainable agricultural practices have substantial, negative environmental impacts (FAO 2016). Environmentally detrimental inputs are overused in the farms, and there is considerable scope for reducing their application with the current technology. Agricultural policies devised to consider both the production and the environmental efficiency of chemical fertilizer may help the farmers to reduce production costs and conserve the environment (Tu et al. 2018).

The concept of efficiency can be traced back to the work of Farrell (1957) where the farm's efficiency was directly measured from observed data based on a single output and multiple inputs. Recently, an environmental efficiency has also got the importance due to the recognition of agriculture effect on the environment. Inputs used in the process of production can influence the environment, either positive or negative. This is an input-oriented single input measure of technical efficiency of the environmentally detrimental input. 'It is the ratio of minimum feasible to observed use of an environmentally detrimental input, conditional on observed levels of the desirable output and the conventional inputs' (Reinhard et al. 1999). There are two basic approaches to measure efficiency, namely stochastic frontier analysis (SFA) and data envelopment analysis (DEA). These approaches are based on parametric and nonparametric methods and apply econometric procedures and mathematical linear programming, respectively. Stochastic frontier analysis makes assumptions regarding the functional form of production functions. This approach can be effectively applied to the data with measurement error, whereas DEA model makes no assumptions regarding the functional form of the model and cannot deal effectively with the presence of measurement error in the data (Tsionas 2003). Stochastic frontier analysis allows not only choosing the best functional form but also includes both random error and statistical noise.

Scores of efficiency measurement are also possible with parametric approach and thus give more accurate results of efficiencies.

Data envelopment analysis (DEA) is a nonparametric method for evaluating efficiency with a set of operating units. Also, in the model, the data envelopment analysis is not considering the error term and cannot test the hypotheses on parameters. Unlike stochastic frontier analysis, efficiency scores cannot be computed for all observations. Data envelopment analysis can be used to compare the projects and policies for production units.

The stochastic frontier approach was recommended for applications in the agriculture sector (Coelli 1995a, b; Ferrara and Vidoli 2017). This approach has the additional advantage to perform tests of hypotheses on parameters about the production structure and the degree of inefficiency. In panel data, stochastic frontier approach deals statistical noise effectively. In this study, we are interested to compute overall technical and environmental efficiency for South Asian countries but also for individual efficiencies as well. So, for that reason stochastic frontier approach is more appropriate than data envelopment analysis for this research study.

In terms of economics, there are three aspects of an efficiency including a technical efficiency, an allocative efficiency and scale efficiency. Technical efficiency can be expressed as the potential of the firm's ability to accomplish the best attainable level of productivity with the given set of inputs. Allocative efficiency refers to the utilization of inputs in the optimum level reflecting on their marginal input costs. It emphasizes on the economic unit capacity to minimize the production cost for a given set of input prices either by reallocating or substituting inputs. Graham (2004) stated it as the proportion of cost efficiency to technical efficiency. De Koeijer et al. (2002) stated technical efficiency as a proportion of real to the most suitable frontier production. There is an idea of producing efficiently by selecting the best combination of input–output vector in the view of prevalent prices of inputs as well as outputs by explaining the allocative and technical efficiency as an overall productive efficiency (Farrell 1957). In distinction, the inefficiency also named as technical inefficiency reflects the failure of producing output with the given inputs and technology. Scale efficiency reflects the optimum range of the operations to diminish cost for long run. Recently, the consideration toward the sustainable environmental condition has increased that emerged the notion of environmental efficiency. Environmental efficiency as the ratio of least achievable to the observed utilization of an environmentally detrimental input restricted to the level of output that has been observed to the conventional inputs (Reinhard et al. 1999; Vu et al. 2019).

Farrell (1957) considered a firm that uses two factors of production X and Y to produce an output R, under the state of constant return to scale. The figure displays a single isoquant YY′ having different combinations of the two factors of production that can be used to produce an output for an efficient firm. R shows the combination of two inputs for the firm that can be used to produce per unit of output. The same level of output having points B and R on the same isoquant is shown on the lower bound of scatter YY' isoquant in Fig. 1. The B displays an efficient combination of two factors that firm uses in the same ratio as R. By using only, a part OB/OR of each input of the firm produces the output same as R, producing maximum amount of OR/OB output from the same inputs. As a result, the technical efficiency of firm is OB/OR. The firm's technical inefficiency is shown by the gap BR that is the quantity by which all factors can be proportionally reduced without decreasing the output. The technically efficient firm uses the ratio equal to 1, while the firm will be inefficient if the ratio is less than 1. The budget line shown in figure by AA′ has sloped that is equivalent to the proportion of two factors of productions' prices. Therefore, the optimal combination of two factors

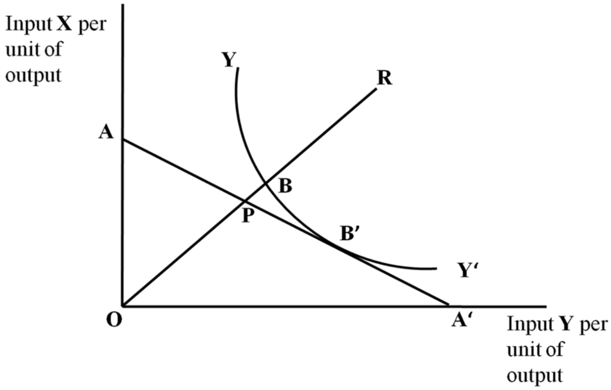

Fig. 1 Technical efficiency (Farrell 1957)

of production is the point where isoquant is tangent to the budget line AA′. The firm is technically efficient at the point B′ with optimum combination of two factors of production. Technical efficiency is a relative concept that provides the level of output relatively to the efficient level of output for the farmer using the same set of inputs. The best efficient production frontier will be one which considers both sided error terms including exogenous factors that are not controlled by the farmers. For the farmers, to produce frontier output level is impossible. Therefore, an extra error term will help to indicate the technical efficiency.

Since last several decades, global warming has been the most crucial environmental issue to the researchers and policy makers. Global warming and environmental degradation are caused by the emission of greenhouse gases (GHGs) such as carbon dioxide (CO2) which is related to the burning of fossil fuels. The environmental contamination including global warming could be controlled by improving the environmental efficiency of chemical inputs in various production processes (Wang et al. 2013). Agriculture sector worldwide contributes a lot in the GHG emissions since the adoption of improved agricultural practices under the concept of green revolution which was introduced during the 1960s (Ullah and Khan 2020). According to the estimates, the agriculture practices contribute 10% to 15% to the global GHG emissions, where Pakistan accounts for 39% of the GHG emissions caused by the global agriculture sector (Abas et al. 2017).

Defining environmental efficiency as the proportion of least feasible to the observed use of an environmentally detrimental input restricted to the level of output that has been observed to the conventional inputs. Environmental efficiency is concerned with a non-radial input measure of technical efficiency that permits for a radial depletion of inputs that are environmentally detrimental. By holding output constant at $Y_{R,}$ Fig. 2 represents the conventional input X of a production function, while Z shows an environmentally detrimental input. In case of a single input, the environmental efficiency is equal to $\left|0Z^F\right|/\left|0Z_R\right|$.

Observed output in Fig. 2 is technically not efficient, as R lies over *F* that is the best practice production frontier. By using an input-conserving orientation, measurement of technical efficiency is possible as the proportion of least feasible input that is used to observe input utilization, restricted to technology and level of observed productivity. Also, it is possible to assess technical efficiency as an output-expanding orientation as the proportion of observed to most achievable output, restricted to technology and usage of observed input. The measure only under the constant return to scale coincides for a technically inefficient producer noted by Färe and Lovell (1978).

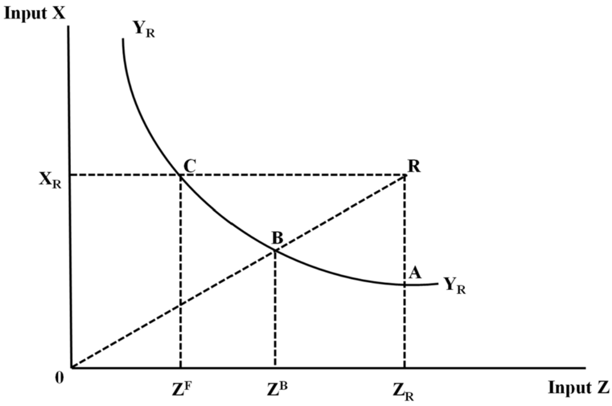

Fig. 2 Production frontier in conventional input X and environmentally detrimental input Z (Reinhard et al. 1999)

Recently, many researchers have employed stochastic frontier analysis (SFA) approach to evaluate the technical and environmental efficiency in various agricultural crop productions; for example, Trang et al. (2018) employed SFA approach to estimate technical and environmental efficiency of farms transforming from sugarcane to shrimp cultivation in the Mekong delta region of Vietnam. The results explored that average technical efficiency was higher than environmental efficiency. In addition, Le et al. (2019) evaluated and compared the technical and environmental efficiency in agricultural production of nine countries in the East Asia during the period from 2002 to 2010. The results explored the difference in the level of technical and environmental efficiency across these countries. Davidova and Latruffe (2020) estimated technical efficiency in Czech Republic by utilizing 88 livestock and 256 crop farms. The results reported that, overall, corporate farms are more technically efficient than the individual crop farms. The study recommended the use of agricultural technology at macrolevel. Gatimbu et al. (2020) evaluated the environmental efficiency of small-scale tea processors in Kenya. The research explored that small-scale tea processors are still environmentally inefficient. They also found that the tea processors could improve 51% environmental efficiency without compromising with the output.

Pais-Magalhães et al. (2020) estimated the environmental efficiency that resulted from waste generation by taking under consideration 15 European economies. The panel analysis had been implemented by adopting the DEA approach covering the time spam 2001–2015. The results showed that Luxembourg, the UK, the Netherlands, Belgium and Sweden were the most environmentally efficient economies as compared to France, Portugal and Austria during 2001–2015. Tu et al. (2019) computed the technical and environmental efficiencies of different rice productions in case of Vietnamese Mekong delta. Survey data involved responses from farmers who implemented eco-friendly or environmental-friendly rice cultivation techniques. The study employed latent class stochastic frontier analysis for the computation of efficiency scores. The findings concluded that overall technical and environmental efficiency scores were 85.02% and 22.58%, respectively. Among individual production methods, floating rice had the highest technical as well as environmental efficiency scores, while ecologically engineered rice had the lowest technical as well as environmental efficiency scores.

Ouyang and Yang (2020) took 27 OECD countries and computed the regional environmental efficiency by using various efficiency estimation analyses. The outcomes of the study showed that the multiplicative model is more reasonable in estimating regional environmental efficiency than the traditional DEA approach. On the other side, the networked analytical structure can give policymakers more detailed analysis findings than single process method. Yang et al. (2020) took Chinese case study and applied some unique efficiency estimation techniques in order to compute production as well as the environmental efficiencies. The study employed by-production (BP) technologies, modeled as an intersection of intended production technologies (production efficiency) and nature's residual-generation technologies (environmental efficiency). The study analyzed data covering the duration 2008–2017. The empirical outcomes demonstrated that BP technologies based on the multiple production relations tend to produce lower efficiency scores than conventional model based on a single production relation. Moreover, BP can be a better choice for the measurement of efficiency index. Liu et al. (2017) also employed a zero-inefficiency stochastic frontier approach for measuring the efficiency and productivity of Thai rice farmers.

The core objective of this study was to conduct comparative analysis of technical and environmental efficiency of agriculture sector in South Asia using the stochastic frontier analysis (SFA) approach developed by Aigner et al. (1977), Meeusen and Broeck (1977) and was later extended to panel data by Pitt and Lee (1981), Battese and Coelli (1988, 1992) and Hjalmarsson et al. (1996) to measure the technical efficiency of agriculture sector. This study has also adopted the methodology developed by Reinhard et al. (1999), Reinhard et al. (2000), Tu et al. (2018), Tu (2017) and Vu et al. (2019) to measure the environmental efficiency of agriculture sector in the South Asian region.

Technology and environment are the most interesting topics for discussions nowadays. Agriculture sector could enhance its productivity by improving both technical and environmental efficiencies. There is a bulk of the literature regarding determination of the factors which affect agricultural productivity or environmental degradation due to farming practices, but there is significant lack of the literature which provides effective and efficient guidelines in order to improve technical and environmental efficiency in rural sector. This is the first-ever comprehensive study to assess comparative analysis of technical and environmental efficiency of agriculture sector in South Asia using balanced panel data. Furthermore, the consideration of the South Asian region also contains a lot of importance due to its rural sector. Almost all the economies in South Asia are agrarian in nature, and their economic growth and development highly depend on their agriculture. Moreover, due to having the status of developing nations, the South Asian economies cannot absorb the pressure of environmental degradation. In this way, this research will be a pioneer attempt in resolving the issues of low agricultural productivity and fast-increasing environmental degradation in South Asia.

This study is conducted to assess the comparative analysis of technical and environmental efficiency of agriculture sector in South Asia using balanced panel data. In addition, this study will help to examine the country's ability to reduce the environmentally detrimental input, fertilizer that is applied in the agriculture sector excessively in South Asian countries. The findings of this study would provide insights into possible improvements in agricultural production toward sustainable development in agriculture. The findings of this research will help the policy makers to develop strategies toward the possible improvement in the production as well as the environmentally friendly and sustainable development in agriculture sector. The comparative analysis of technical and environmental efficiency of agriculture sector in South Asia will provide the information to the environmentally inefficient countries for improving agricultural and environmental policies to achieve sustainable development in agriculture. No work has been done regarding technical and environmental efficiency of agriculture sector in the context of South Asian countries using parametric approach stochastic frontier analysis. In this study, we have used econometric approach for computing not only the technical and environmental efficiency, but also interactive contribution of inputs used in the production. The study had exhibited the variation among the technical and environmental efficiency of South Asian countries and identifies those who are technically and environmentally efficient. Also, their experiences will help each other for sustainable agricultural development.

2 Methodology

The purpose of this study was to estimate technical and environmental efficiency of agriculture sector in South Asia using balanced panel data over the period of 2002 to 2016. The data for output, land and fertilizer were collected from Food and Agriculture Organization (FAO 2018). The data for labor were taken from International Labour Organization (ILO 2018), while for capital, data were used from World Bank (2019). Variables included in this study are based on a previous study conducted by Moreno-Moreno et al. (2018). Figure 1 gives map of South Asian countries (Fig. 3).

Fig. 3 South Asia Map

The value of gross agriculture production was taken as an output denoted by (Y). Land, labor, capital stock and fertilizer were used as independent variables denoted by (X) where fertilizer was incorporated as an environmentally detrimental input that is why it is denoted by (Z). Descriptions of the variables used in this study are given in Table 1.

In this research study, land includes the collective of arable land, land under permanent crops and land under permanent meadows and pastures measured in thousand hectares. Labor is taken as total economically active population in agriculture sector expressed in thousands of people. Capital stock is calculated as gross fixed capital formation in agriculture sector expressed in thousand US dollars, based on the constant price of 2010. Fertilizer consumption refers to the total quantity of three key nutrients including phosphate (P_2O_5), nitrogen (N) and potash (K_2O). It is expressed in thousands of tons. It is used as an environmentally detrimental input in this study rather than as an undesirable output or bad in this study.

Technical efficiency can be measured in two ways: either as an output-oriented where it is taken as a ratio of observed to maximum achievable output that is conditional on the usage of observed level of inputs and technology or as an input-sustaining orientation where the ratio of minimum feasible inputs is used to observed input use that is conditional on observed output production and technology (Reinhard et al. 1999). Environmental efficiency can also be incorporated in two different ways in technical efficiency measurement. Environmental impacts can be modeled as a bad or undesirable output in the process of production by integrating quantifiable environmental impacts into the vector of output and then get an inclusive technical efficiency measures (Pittman 1983 and Färe et al. 1989). As an input-oriented efficiency, environmental effect can be demonstrated as a conventional input where degradation effects on environment are the outcome from the use of environmentally detrimental inputs (Reinhard et al. 1999; Pittman 1981; Tu et al. 2018; Tu 2017; Vu et al. 2019).

In this research study, technical efficiency is estimated in the conventional way, as the ratio of observed to maximum feasible output referred to an output-oriented measure generally written as under:

$$TE_R = \left[\max\{\emptyset : \emptyset Y_R \leq F\left(X_R, Z_R\right)\}\right]^{-1} = \left|0Y_R\right| / \left|0Y^F\right|, \quad (1)$$

while environmental efficiency is estimated as the ratio of least feasible to observed use of the environmentally detrimental input that is conditional to the observed levels of desirable output and the conventional inputs. Here, a non-radial input-oriented single factor measurement of technical efficiency of the environmentally detrimental input is used which is reasonable in this study (Kopp 1981). It can be written as

Table 1 Description of the variables used in this study

Variables	Description
Output	Value of the gross agricultural production measured in million US dollar, based on the constant price of 2010
Land	Agricultural land measured in thousand hectares
Labor	Total economically active population in agriculture measured in thousands of people
Capital	Gross fixed capital stock measured in thousand US dollars, based on the constant price of 2010
Fertilizer	Consumption of fertilizer (nitrogen N, potash K_2O and phosphate P_2O_5) measured in thousands of tons

$$EE_R = \left[\min\left\{\theta : F\left(X_R, \theta Z_R\right) \geq Y_R\right\}\right] = \left|0Z^F\right| / \left|0Z_R\right| \tag{2}$$

First, econometric techniques were used to find efficiency estimates. The stochastic frontier analysis (SFA) approach is used that was simultaneously introduced by Aigner et al. (1977), Meeusen and Broeck (1977) and was later extended to panel data by Pitt and Lee (1981), Battese and Coelli (1988, 1992) and Hjalmarsson et al. (1996) to measure the technical efficiency of agriculture sector. This study has used only a single output and estimated a stochastic production frontier to relate the environmental performance of countries to the best practice of environment-friendly agriculture in South Asian region.

Second, this study also adopted approach developed by Reinhard et al. (1999), Reinhard et al. (2000), Vo et al. (2015), Tu (2017), Tu et al. (2018), Tu (2017) and Vu et al. (2019) to determine the environmental efficiency of agriculture sector in South Asia where the environmental influence is modeled as a conventional input. Surplus fertilizer (nitrogen N, potash K_2O and phosphate P_2O_5) in this study is modeled as an environmentally detrimental input in the stochastic translog production frontier model.

Third, technical efficiency and environmental efficiency estimates are provided separately in this study analysis. As technical efficiency is measured as an output-oriented, whereas environmental efficiency is an input-oriented measure as it emphasizes on single environmental detrimental input, this requires a stochastic translog production frontier to reduce misspecification error. Therefore, the study also used maximum likelihood ratio for the choice of correct model. STATA software version 13 is used to measure a translog stochastic production frontier model for measuring technical efficiency and environmental efficiency scores of South Asian countries. The details of methods are given below.

In SFA, a two-parameter by an additional error term is used to model inefficiency. A stochastic production frontier is generally expressed as under:

$$Y_{it} = f\left(X_{it,} Z_{it,} \alpha, \beta, \xi\right) * \exp\left\{V_{it} - U_{it}\right\} \tag{3}$$

where all countries are indexed with a subscript i and all years are indexed with a subscript t.

Y_{it} = level of gross agricultural production measured in million US dollar. X_{it} = vector of conventional inputs (X_{it1} = land, X_{it2} = labor, X_{it3} = capital stock) used by the countries. Z_{it} = vector of environmentally detrimental input (Z_{it} = fertilizer, i.e., nitrogen N, potash K_2O and phosphate P_2O_5). α, β and ξ = parameters of the model to be estimated. V_{it} = random error term that is independent, identical and normally distributed as $V_{it} \sim N\ (0, \sigma_v^2)$, that intends to reflect the influence of exogenous events which are beyond the control of farmers. U_i = nonnegative statistical noise which is assumed to describe the effect of technical inefficiencies in production. Also, it is independently and identically distributed as $U_{it} \sim N^+\ (\mu, \sigma_u^2)$.

TE_{it} gives the technical efficiency and is referred as the ratio of observed output to maximum feasible output. The stochastic version of output-oriented technical efficiency (TE) is expressed as:

$$TE_{it} = \frac{Y_{it}}{f\left(X_{it}, Z_{it}; \alpha, \beta, \xi\right) \exp\left(V_{it}\right)} = \exp\left(-U_i\right) \tag{4}$$

The country gets the maximum feasible output when TE = 1; and TE < 1 gives a measure of the deficit of the observed output from maximum feasible output.

In order to derive the stochastic version for Eq. 2 of the environmental efficiency measure, it is important to choose the right functional form. As in this research, we are using econometric approach, i.e., stochastic frontier approach. It is recommended that the decision regarding functional form must be made on numerous alternative models and select the preferred one based on likelihood ratio (Coelli 1996). The SFA being a parametric approach requires the assumption of a function form a priori, and the frontier is estimated econometrically by maximum likelihood approach (Coelli et al. 2005). To choose between the Cobb–Douglas model and translog model is important, as they are most common functional forms that have been used in empirical studies of production including frontier analysis (Battese and Broca 1997). Both Cobb–Douglas and translog production function can be accommodated by SFA. The SFA functional form can be decided by testing the competence of the Cobb–Douglas comparative to the less restrictive translog model under the null hypothesis, i.e., Cobb–Douglas is the correct functional form. In SFA model, the parameters of Cobb–Douglas and translog model are estimated by maximum likelihood approach, based on the values of likelihood ratio for both the models, and will lead to acceptance of appropriate model.

A Cobb–Douglas stochastic frontier model takes the form:

$$InY_{it} = \alpha_o + \sum_j \alpha_j InX_{itj} + \sum_k \beta_k InZ_{it} + V_{it} - U_i, \tag{5}$$

A translog stochastic frontier model takes the form of Eq. (6):

$$\begin{aligned} InY_{it} = \alpha_o &+ \sum_j \alpha_j InX_{itj} + \beta_k InZ_{it} + \frac{1}{2}\sum_j \sum_l \alpha_{jl} InX_{itj} InX_{itl} + \frac{1}{2}\beta_{kk}(InZ_{it})^2 \\ &+ \sum_j \sum_k \xi_{jk} InX_{itj} InZ_{it} + V_{it} - U_i \end{aligned} \tag{6}$$

where $\xi_{jk} = \xi_{kj}$. When U_i is equal to zero and technical efficient country is producing logarithm of the output $Y^{\cdot}_{it}$ by utilizing X_{it} and Z_{it} in Eq. 6, the translog SFA for technical efficient country can be specified as:

$$\begin{aligned} InY^{\cdot}_{it} = \alpha_o &+ \sum_j \alpha_j InX_{itj} + \beta_k InZ_{it} + \frac{1}{2}\sum_j \sum_l \alpha_{jl} InX_{itj} InX_{itl} + \frac{1}{2}\beta_{kk}(InZ_{it})^2 \\ &+ \sum_j \sum_k \xi_{jk} InX_{itj} InZ_{it} + V_{it} \end{aligned} \tag{7}$$

In a model, environmentally detrimental input Z_{it} is replaced by Z_{it} and if the environmentally efficient country is utilizing X_{it} and Z_{it} for producing $Y_{it}{}^F$, then the equation becomes

$$\begin{aligned} InY^F_{it} = \alpha_o &+ \sum_j \alpha_j InX_{itj} + \beta_k InZ_{it} + \frac{1}{2}\sum_j \sum_l \alpha_{jl} InX_{itj} InX_{itl} + \frac{1}{2}\beta_{kk}(InZ_{it})^2 \\ &+ \sum_j \sum_k \xi_{jk} InX_{itj} InZ_{it} + V_{it} \end{aligned} \tag{8}$$

where $Y^{\cdot}_{it}$ is equal to Y^F_{it} and $InZ_{it} - InZ_{it}$ is equal to the logarithm of stochastic environmental efficiency $InEE_{it}$. To solve Eqs. 6 and 8 yields

$$\frac{1}{2}\beta_{kk}[(InZ_{it})^2 - \left(InZ_{it})^2\right] + \sum_j \sum_k \xi_{jk} InX_{itj}\left[\left(InZ_{it}\right) - \left(InZ_{it}\right)\right] + \beta_k\left[\left(InZ_{it}\right) - \left(InZ_{it}\right)\right] + U_i = 0 \tag{9}$$

Rewrite this equation as

$$\frac{1}{2}\beta_{kk}[\left(InZ_{it}\right) - \left(InZ_{it}\right)]^2 + \left[\beta_k + \sum_j \sum_k \xi_{jk} InX_{itj} + \beta_{kk} InZ_{it}\right]\left(InZ_{it}\right) - \left(InZ_{it}\right) + U_i = 0 \tag{10}$$

For solving $InEE_{it} = \left(InZ_{it}\right) - \left(InZ_{it}\right)$, the following equation can be obtained

$$InEE_{it} = \left[-\left(\beta_k + \sum_j \sum_k \xi_{jk} InX_{itj} + \beta_{kk} InZ_{it}\right) \pm \left\{ \left(\beta_k + \sum_j \sum_k \xi_{jk} InX_{itj} + \beta_{kk} InZ_{it}\right)^2 - 2\beta_{kk} U_i \right\}^{.5} \right] / \beta_{kk} \tag{11}$$

Reinhard et al. (2000) and Vu et al. (2019) stated that environmental efficiency is measured with the '$+\sqrt{}$' formula on Eq. (11) to measure the environmental efficiency because the technically efficient country is essentially environmentally efficient.

The estimation of parameters regarding the fitness of frontier model is tested by applying the maximum likelihood–ratio estimator. The comparison between the two models, i.e., Cobb–Douglas and translog, is based on statistics of likelihood ratio (Coelli et al. 2005) written as

$$\lambda = -2\left\{In\left[L\left(H_0\right)\right] - In\left[L\left(H_1\right)\right]\right\}$$

where λ = Likelihood ratio and $In\ [L\ (H_0)]$ gives the value of the logarithm of likelihood ratio of the Cobb–Douglas model with restrictions, i.e., H_0 assumes that Cobb–Douglas model is most appropriate model. $In\ [L\ (H_1)]$ = the value of the logarithm of likelihood ratio of the translog model without restrictions, i.e., H_1 assumes that translog model is most suitable model for this study. The maximum likelihood ratio assumes Chi-square distribution (χ^2) (Coelli et al. 1998).

For the estimation of both appropriate SFA model and technical inefficiency, the likelihood method was used (Coelli et al. 2005). Log likelihood test helps to find out whether the effect of inefficiency is needed to be included or not. Log likelihood test allows the parameter of error variance ratio known as gamma (γ) and sigma square (σ^2) expressed as $\sigma^2_w = \sigma^2_v + \sigma^2_u$ and $\gamma = \sigma^2_u / \sigma^2_w$ (Battese and Coelli 1992). The sigma square value measures the goodness of data fit in the model, while the value of gamma lies 0 to 1. The value $\gamma = 0$ shows the noise effect, while $\gamma = 1$ shows inefficiency effect. This estimation involves checking null hypothesis (H_o) under the statement of that 'there are no effects of technical inefficiency exist in the countries' expressed as $\gamma = 0$ against alternative hypothesis (H_a) that 'there exists technical inefficiency in the countries' as $\gamma = 1$.

3 Results and discussion

Table 2 illustrates the descriptive statistics of variables included in this study. The results of South Asian countries show some phenomenal outcomes. The figures illustrate that India has the highest mean gross agricultural output that is 279,123.80 in million US dollar

Table 2 Descriptive statistics of the variables

Variables	Bangladesh	Bhutan	India	Nepal	Pakistan	Sri Lanka
Output						
Mean	18,587.38	267.78	279,123.80	5227.56	40,168.54	4610.90
Maximum	23,953.84	318.75	347,109.20	6218.06	46,975.30	5923.39
Minimum	13,308.72	234.21	213,270.90	4144.54	31,316.52	3567.40
Std. dev	3534.32	24.75	41,274.0	709.87	5165.31	843.98
Land						
Mean	9227.49	538.62	179,893.80	4159.24	36,086.20	2565.40
Maximum	9353.00	593.00	180,560.00	4241.00	36,884.00	2740.00
Minimum	9099.00	519.00	179,573.00	4121.00	35,242.00	2310.00
Std. dev	86.59	26.60	307.52	44.05	525.97	162.19
Labor						
Mean	26,400.97	208.11	232,539.80	10,314.02	22,865.97	2529.55
Maximum	27,905.96	221.10	249,562.80	11,693.50	27,798.53	2731.69
Minimum	24,938.37	192.27	214,959.90	9020.36	17,066.66	2227.92
Std. dev	888.77	8.83	13,272.16	783.05	3214.01	164.35
Capital						
Mean	0.35	2.60	0.78	0.41	1.61	1.02
Maximum	0.37	3.00	0.84	0.47	2.16	1.23
Minimum	0.33	2.35	0.72	0.35	1.33	0.88
Std. dev	0.01	0.18	0.04	0.03	0.26	0.13
Fertilizer						
Mean	1,740,144.00	1292.60	23,422,005.00	59,739.58	3,786,626.00	290,803.90
Maximum	2,311,680.00	2396.00	28,373,686.00	156,654.00	4,480,006.00	399,291.20
Minimum	1,318,676.00	1010.00	16,095,991.00	3030.00	3,043,040.00	171,499.40
Std. dev	329,373.20	331.96	3,963,690.00	56,748.77	420,727.8	57,297.48

among the six countries of South Asia included in this study. The value of mean agricultural output was trailed by Pakistan, Bangladesh, Nepal, Sri Lanka and Bhutan with their respective values as 40,168.54, 18,587.38, 5227.56, 4610.90 and 267.78 in million US dollar. The same pattern has been observed among the countries for utilizing agricultural land. Comparing the labor force used in agriculture sector, India is using on an average more labor force, while Bangladesh is on second place. The mean values of agricultural labor force for the rest of the countries are followed by Pakistan, Nepal, Sri Lanka and Bhutan. It is again interesting to note that the highest mean value of capital used in agriculture sector is associated with Bhutan that is 2.60 thousand US dollars as compared to other countries, while the output is least as compared to other South Asian countries. The mean values of capital used for the rest of the countries are followed by Pakistan, Sri Lanka, India, Nepal and Bangladesh. The highest mean value of fertilizer is estimated for India, i.e., 23,422,005.00 thousand tons, while the other countries can be ranked, respectively, based on values estimated that is Pakistan, Bangladesh, Sri Lanka, Nepal and Bhutan.

By summarizing the descriptive statistics, it is observed that with the highest average utilization of inputs land, labor and fertilizer, India is producing highest gross agricultural output but using less capital as compared to Bhutan, Pakistan and Sri Lanka, while Bhutan is producing less gross agricultural output with the highest capital utilization as compared to other South Asian countries included in this study.

To check the existence of the effect of technical inefficiency is important before estimating the best model (Coelli et al. 2005). For this purpose, LL test (log likelihood test) was used. This estimation involves checking null hypothesis (H_o) under the statement of that 'there are no effects of technical inefficiency exist in the countries' expressed as $\gamma = 0$ against alternative hypothesis (H_a) that 'there exists technical inefficiency in the countries' as $\gamma = 1$. The LL test value is 175.72 which is statistically significant and exceeds 1% from the critical value. This result suggested to accept the alternative hypothesis and concluded that there are effects of technical inefficiencies.

To choose the best-fitted model of production between the Cobb–Douglas and translog, the likelihood ratio (LR) is used (Coelli et al. 2005). The hypothesis was tested using the null hypothesis (H_o) that Cobb–Douglas production model is best against the alternative hypothesis (H_a) that translog production model is more appropriate for this study. The estimated value of likelihood ratio test that follows Chi-square distribution is 716.16 which is statistically significant at 1% as it exceeds from the critical value 23.21 having 10 degrees of freedom (Carrer et al. 2015; Ullah et al. 2017). Here, translog production function against Cobb–Douglas production function was accepted. Translog production function contains some strengths over the Cobb–Douglas production function; for example, unlike

Table 3 Results of translog stochastic frontier model

Variable	Parameter	Coefficient	Std. dev	Prob
Constant	α_{it0}	33.834 *	6.40	<0.01
In ld	α_{it1}	3.669 *	0.73	<0.01
In la	α_{it2}	0.717	0.60	0.234
In cs	α_{it3}	−3.419 *	0.84	<0.01
In f	β_{it1}	0.464	0.44	0.291
½(In ld)²	α_{it11}	0.195	0.25	0.442
½(In la)²	α_{it22}	0.129	0.13	0.312
½(In cs)²	α_{it33}	0.122 *	0.03	<0.01
½(In f)²	β_{it11}	0.019	0.02	0.227
In ld In la*	α_{it12}	−0.107	0.16	0.513
*In ld*In cs*	α_{it13}	−0.177 *	0.05	<0.01
In ld In f*	ξ_{it11}	0.023	0.05	0.609
*In la*In cs*	α_{it23}	−0.017	0.04	0.678
In la In f*	ξ_{it21}	−0.028	0.03	0.323
In cs In f*	ξ_{it31}	−0.027	0.02	0.299
Model diagnostics				
/ Insigma2	σ^2	−4.46*		<0.01
Gamma	Γ	0.924		
Sigma_u²	σ_u^2	0.011		
Sigma_v²	σ_v^2	0.00088		
/eta	H	0.159*		<0.01
/mu	μ	−0.465		0.218
Log likelihood		175.71		
Wald χ^2value (13)		2536.89		<0.01

Note * shows 1% significant level

the Cobb–Douglas production function, the translog production function does not assume rigid premises like perfect substitution of production inputs. Furthermore, the Cobb–Douglas production function always assumes constant returns to scale, which is not possible in real life, and the translog production function does not have such deficiency.

The STATA software was used to run the regression for translog stochastic frontier production model, and the results are provided in Table 3. The variables land, labor, capital and fertilizer are abbreviated as *ld, la, c* and *f*, respectively. The positive value of eta (η) 0.159 also helps to testify the alternative hypothesis (H_a: $\eta \neq 0$) significantly that the level of technical efficiencies that vary over the period of time oppose to null hypothesis (H_o: $\eta = 0$) that the level of technical efficiency is insignificant to time.

As the results of the estimated factors coefficients given in Table 3 do not help in direct interpretation of the results, for that reason, output elasticities regarding inputs are computed which is shown in Table 4. The output elasticity with respect to inputs was estimated. The sign for the elasticity coefficients for land, labor, capital and fertilizer is positive. The sum of the elasticity coefficient is 3.57 which is greater than one representing increasing returns to scale that clearly illustrated that the agricultural production is an increasing function of inputs. The results are somewhat like Reinhard et al. (1999, 2000), Mathij and Swinnen (2001) and Ajibefun and Adenegan (2008). The land has on average highest elasticity, i.e., 2.13, while labor, fertilizer and capital elasticities are 1.26, 0.17 and 0.01, respectively. It also shows that the six South Asian countries can increase the production as there is a substantial room for increasing agricultural productivity. Increasing returns means that countries are benefited with economies of scale that are related to the incentives given to the farms of countries (Johnson et al. 1994). Land shows the highest elasticity, but this input is naturally fixed. This finding is in line with the result of Liu et al. (2019) and Sriboonchitta et al. (2017). The land area cannot be increased, but the uncultivated lands can be used for the agricultural production. Farrell and Fieldhouse (1962) related scale economies to the higher persistent level of output and stressed that indivisible labor used in the agricultural production is exhausted to reach the optimum level of output if the capital is not utilized efficiently. It is somehow true by comparing the elasticities results for land, labor, fertilizer and capital where the contribution of capital is least among all the inputs.

The estimated values of output-oriented technical efficiency of the translog stochastic production model scores are presented in Table 5. The findings reveal that the mean scores for South Asian technical efficiency are 0.92 that suggests that agricultural production of south Asian countries could be further increased up to 8 percent by eliminating the effects of technical inefficiency. On average, all the South Asian countries scores of technical efficiencies are closest from 0.85 to 0.99. It is quite interesting from the findings that Sri Lanka is the most efficient country having 0.99% technical efficiency scores, while the rest of the scores of South Asian countries technical efficiency are followed by India, Bhutan, Bangladesh, Nepal and Pakistan with 0.98, 0.93, 0.89, 0.88 and 0.85, respectively. The

Table 4 Results of output elasticity and return to scale

Variables	Values
Land	2.13
Labor	1.26
Capital	0.01
Fertilizer	0.17
Return to scale	3.57 > 1

Table 5 Time-varying technical efficiency scores

Year	Bangladesh	Bhutan	India	Nepal	Pakistan	Sri Lanka	Mean
2002	0.76	0.85	0.97	0.74	0.67	0.98	0.83
2003	0.79	0.87	0.98	0.77	0.71	0.98	0.85
2004	0.82	0.89	0.98	0.80	0.75	0.99	0.87
2005	0.84	0.9	0.98	0.83	0.78	0.99	0.89
2006	0.86	0.92	0.98	0.85	0.81	0.99	0.90
2007	0.88	0.93	0.99	0.87	0.83	0.99	0.92
2008	0.90	0.94	0.99	0.89	0.86	0.99	0.93
2009	0.91	0.95	0.99	0.91	0.88	0.99	0.94
2010	0.93	0.95	0.99	0.92	0.89	0.99	0.95
2011	0.94	0.96	0.99	0.93	0.91	1	0.95
2012	0.95	0.97	0.99	0.94	0.92	1	0.96
2013	0.95	0.97	0.99	0.95	0.93	1	0.97
2014	0.96	0.98	1	0.96	0.94	1	0.97
2015	0.97	0.98	1	0.96	0.95	1	0.98
2016	0.97	0.98	1	0.97	0.96	1	0.98
Mean	0.90	0.93	0.98	0.89	0.85	0.99	0.92
Std. dev	0.07	0.04	0.01	0.07	0.09	0.01	0.05
Rank	4	3	2	5	6	1	

highest scores represent that these countries are producing more by utilizing least of its country's resources. The results also indicate that maximum technical efficiency has been achieved by Sri Lanka from 2004 while India from 2007. There is an increasing trend in technical efficiency scores among all the countries.

Technical inefficiency of 8% in the region could be due to the utilization of orthodox farming practices. Modern and advanced production strategies in agriculture are required to fill the gap of technical inefficiency. Almost all the economies in South Asia are under-developed, and they highly depend on their agricultural sector. Being the developing economies, these countries have several hurdles in the way to use the advanced farming practices. The biggest constraint has been recognized as the financial constraints. The farmers in this region are very poor, and they cannot afford the cost of improved farming techniques. That is why they still use comparatively old farming methods. Moreover, lack of farmers' skills and knowledge is also solid reasons of this technical inefficiency. Results show that Sri Lanka has the highest technical efficiency score (99%) as compared to other countries in the region. This shows the greater interest of government and policy makers toward the agriculture sector in Sri Lanka. Pakistan is at the bottom based on technical efficiency with 85% in South Asia. This is quite unexpected because agriculture is the largest sector of Pakistan's economy and it contributes 18.9% to GDP. Findings of the technical efficiency reveal a weak agriculture system in Pakistan, and this needs to be improved.

The results of input-oriented environmental efficiency scores using the translog stochastic frontier model are illustrated in Table 6. The average score of environmental efficiency of South Asia is 0.77. On average, all the South Asian countries scores of input-oriented environmental efficiency are ranging from 0.57 to 0.97 which shows that there is yet extensive opportunity to get better in environmental efficiency of South Asian countries. The ranking of technical efficiency and environmental efficiency is identical except for Pakistan

Table 6 Time-varying environmental efficiency scores

Year	Bangladesh	Bhutan	India	Nepal	Pakistan	Sri Lanka	Mean
2002	0.41	0.42	0.92	0.25	0.34	0.94	0.55
2003	0.46	0.48	0.93	0.22	0.40	0.94	0.57
2004	0.52	0.54	0.94	0.32	0.46	0.95	0.62
2005	0.58	0.61	0.95	0.31	0.52	0.96	0.65
2006	0.62	0.65	0.96	0.41	0.57	0.97	0.70
2007	0.67	0.70	0.96	0.34	0.62	0.97	0.71
2008	0.71	0.72	0.97	0.38	0.66	0.98	0.74
2009	0.74	0.78	0.97	0.65	0.71	0.98	0.81
2010	0.78	0.77	0.98	0.70	0.75	0.98	0.83
2011	0.81	0.81	0.98	0.75	0.78	0.98	0.85
2012	0.83	0.83	0.98	0.78	0.81	0.99	0.87
2013	0.86	0.87	0.99	0.82	0.84	0.99	0.89
2014	0.88	0.88	0.99	0.85	0.86	0.99	0.91
2015	0.89	0.90	0.99	0.87	0.88	0.99	0.92
2016	0.91	0.91	0.99	0.89	0.89	0.99	0.93
Mean	0.71	0.72	0.96	0.57	0.67	0.97	0.77
Std. dev	0.16	0.15	0.02	0.24	0.17	0.02	0.13
Rank	4	3	2	6	5	1	

and Nepal which shows that as compared to Nepal, Pakistan is an environmentally efficient country. The scores of environmental efficiency ranked Sri Lanka first with 0.97 while India second with 0.96 with a minor difference of 0.01. However, input-oriented environmental efficiency scores for Bhutan, Bangladesh, Pakistan and Nepal are trailed, respectively, with the scores of 0.72, 0.71, 0.67 and 0.57.

The insights of Table 6 illustrate that farmers and policy makers in Sri Lanka and India take care of environmental contamination along with increase in the agricultural productivity. Therefore, the remaining economies are comparatively environmentally inefficient as compared to these countries. Almost all the economies in this region are agrarian in nature, and agriculture is responsible for environmental degradation worldwide due to the emissions of greenhouse gases (GHGs). Farmers in South Asian region use machinery and other chemical inputs in order to enhance the agricultural productivity, but these practices become harmful for the environment. This issue could be solved by using fuel efficient machinery and by replacing fuel-based machinery with electricity-based machinery in agriculture. Also, farmers should be given proper education and training regarding the most appropriate use of chemical fertilizers and pesticides in the region. Control on environmental degradation will also be beneficial for the agricultural productivity as suitable environment is a desirable situation for the farmers. By comparing Tables 5 and 6, it is concluded that the intensions of farmers in South Asia are more toward the enhancement of agricultural productivity, not toward controlling the environmental degradation as the average technical efficiency score is 92% and the average environmental efficiency score is 77% in South Asia. Commercial farming forces the farmers to use excessive amount of chemical inputs and machinery in the agriculture, and this deteriorates the existing environmental situation in the region. Long et al. (2018) also explored that fertilizer intensity negatively affects environmental efficiency of agriculture sector.

Table 7 Summary of technical and environmental efficiency scores

	Mean	Maximum	Minimum	Std. dev
Technical efficiency	0.92	0.97	0.82	0.05
Environmental efficiency	0.77	0.93	0.54	0.13

The results suggest reduction of fertilizer which is taken as an environmentally detrimental input up to 0.23 without the trading off conventional inputs; the South Asian countries can achieve the environmental efficiency. Technical efficiency is assumed to be both essential and sufficient for environmental efficiency (Reinhard et al. 1999). Table 7 summarizes the summary statistics of technical and environmental efficiency. The mean values of technical and environmental efficiency show the evidence that South Asian countries are on average regarded as technically and environmentally efficient. It is shown in the results that technical and environmental efficiencies are positive related. It was found that on average, South Asian countries have reached the maximum level of technical efficiency that is 92% and have potential to raise the agricultural production up to 8% by eliminating the inefficiency effects with the given inputs and available technology. Also, the mean value of the environmental efficiency of South Asian countries using only fertilizer as a single environmentally detrimental input is 0.77, i.e., 77%. It shows that without trading off the agricultural output, the South Asian countries can decrease the utilization of fertilizer by 23% to achieve environmental efficiency. These findings are consistent with the findings of Tirado et al. (2017) and Tu et al. (2018).

4 Conclusions and recommendations

This study was conducted to measure and assess the comparative analysis of technical and environmental efficiency of agriculture sector in South Asia. The analytical framework was developed to calculate output-oriented technical efficiency and input-oriented environmental efficiency using single environmentally detrimental input fertilizer as well as conventional inputs in the model. The balanced panel data have been used for six South Asian courtiers including Bangladesh, Bhutan, India, Nepal, Pakistan and Sri Lanka from 2002–2016, while Afghanistan and Maldives are excluded in this study due to limitations. As the stochastic frontier approach allows the estimation of output-oriented technical efficiency using a single output in a model, econometric approach was used to transform the SFA into translog stochastic frontier model to the analysis of input-oriented environmental efficiency modeling fertilizer as an only environmentally detrimental input. It is the advantage to treat environmentally detrimental input as a convention input with least adaptation in existing methods to the estimation of efficiency (Pittman 1981; Cropper and Oates 1992). It was found that on average, South Asian countries have reached the maximum level of technical efficiency that is 92% and suggested to raise the agricultural production up to 8% by eliminating the inefficiency effects with the given inputs and available technology. Also, the mean value of the environmental efficiency of South Asian countries using only fertilizer as a single environmentally detrimental input is 0.77, i.e., 77%. It shows that without trading off the agricultural output, the South Asian countries can decrease the utilization of fertilizer by 23% to achieve environmental efficiency. If the South Asian countries want to improve their environmental efficiency, they have to reduce the environmentally detrimental inputs (fertilizer). The farmers' behavior toward the conventional inputs is more predictable than the environmentally detrimental input. There is an indication from the results that countries could improve their technical efficiency being further environmentally efficient by preferring input that are less detrimental to the environment. There is a need to invest and must be further researches that will help South Asian countries to improve agricultural productivity and sustainable growth. The extension services must be provided to the farmer to be aware about the environmental efficiency and the negative impacts on the environment and improve their performance.

From the results of return to scale, it is recommended that the land contributed the most, so it is important that regulatory framework must be strengthening for leasing lands that are not cultivated efficiently from less efficient producers to more efficient ones. For efficient land marketing, the better administration is required that also motivates the owners to lease their land for agricultural productivity. There is a need to focus on providing extension services that will help the farmers to know about the land quality, using advanced technology and awareness about the use of fertilizer according to the need of the land of the area for different crops and about the varieties of crops that can be cultivated. In agriculture sector, credit facilities must be provided to the farmers for capital purchase and government should provide better technology and machinery on lease as well that should be affordable to farmer. Using fertilizer in some places could be necessity but which kind of fertilizer is suitable for the region and according to the land requirement; otherwise, it may cause the land degradation as well. The knowledge about the cultivated crops and its fertilizer requirement is also important. It is recommended that there must be collaboration among the South Asian countries in research and development especially in agriculture sector on priority bases.

Compliance with ethical standards

Conflict of interest The authors declared no potential conflicts of interest with respect to authorship and/or publication of this article.

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