ADBI Working Paper Series

REGIONAL COOPERATION FOR IMPROVING AGRICULTURE PRODUCTION EFFICIENCY: A STRATEGIC TOOL FOR EMISSION REDUCTION

Kazi Arif Uz Zaman

No. 1301
January 2022

Asian Development Bank Institute

Kazi Arif Uz Zaman is deputy general manager at the Financial Stability Department of Bangladesh Bank (the central bank of Bangladesh) in Motijheel, Dhaka, Bangladesh.

Suggested citation:

Zaman, K. A. U. 2022. Regional Cooperation for Improving Agriculture Production Efficiency: A Strategic Tool for Emission Reduction. ADBI Working Paper 1301. Tokyo: Asian Development Bank Institute. Available: https://www.adb.org/publications/regional-cooperation-for-improving-agriculture-production-efficiency-a-strategic-tool-for-emission-reduction

Please contact the authors for information about this paper.

Email: kazi.arif@bb.org.bd

This study has not received any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Asian Development Bank Institute
Kasumigaseki Building, 8th Floor
3-2-5 Kasumigaseki, Chiyoda-ku
Tokyo 100-6008, Japan

Tel: +81-3-3593-5500
Fax: +81-3-3593-5571
URL: www.adbi.org
E-mail: info@adbi.org

Abstract

The growing population and climatic uncertainties have compelled producers to undertake faster exploitation of the resources in agricultural production to meet global food security, which, in turn, leads towards unsustainable and input-led inefficient production growth. The problem is further exacerbated by the increasing emission of GHGs from this production process. This paper suggests a solution to this by advocating the role of regional cooperation to increase the technical efficiency level in the agricultural production of countries through technology transfer, knowledge sharing, capacity building, and adequate investment under the regional cooperation framework. Concurrently, this study links this improvement of production efficiency with the reduction of emissions both theoretically and empirically for all Asian subregions. This paper first adopts the stochastic frontier model—a widely used statistical technique that frames the production functions while estimating the inefficiencies of economic units. Using 2010–2016 panel data on agriculture production and five inputs—land, labor, capital, fertilizer, and energy—this paper estimates the agriculture production efficiencies of the countries under five Asian subregions. Estimations reveal that West Asia, Southeast Asia, South Asia, East Asia, and Central Asia have agriculture production efficiencies of 70%, 85%, 66%, 92%, and 76%, respectively. Following the estimations and other calculations, this study reveals that with concerted efforts towards optimizing production efficiencies under (sub)regional cooperation frameworks, an annual emission of 384.5 megatons of CO2eq GHG could have been reduced in Asia while keeping the production at the current level. The potential reduction of emissions equals 16.8% of Asia’s total emissions originating from agricultural activities and 7.1% of that of global emissions.

Keywords: agriculture production efficiency, regional cooperation, stochastic frontier model, emission reduction, Asian subregions

JEL Classification: R11, F53, O47, O53, Q15, Q56

Contents

1. INTRODUCTION 1

2. RECENT STATES OF AGRICULTURAL PRODUCTION AND EMISSIONS IN ASIA 4

2.1 Inadequate Production to Meet Regional Agricultural Demand 4
2.2 Growing Emission from Agriculture 5

3. METHODOLOGY 5

3.1 Stochastic Frontier Model 6
3.2 Model Specification for Production Efficiency 7
3.3 Linking Production Efficiency and Emission Reduction Potential 8
3.4 Rationale for Choosing the Input Variables 9

4. DESCRIPTION OF DATA 10

5. RESULTS AND FINDINGS 11

5.1 Summary Statistics 11
5.2 Estimation of the Coefficients 12
5.3 Estimations of Production Efficiency and Potential Emission Reduction 13

6. POLICY IMPLICATIONS 16

7. CONCLUSION 18

APPENDIX 19

REFERENCES 20

1. INTRODUCTION

Agriculture is the primary sector of an economy. The majority of the low-skilled laborers of a country are usually deployed in the agriculture production process (Shen and Liu 2016; Dun, Klocker, and Head 2018). Adequate investment and efficiency enhancement approaches are adopted in this sector, but at a slower pace than in the other sectors of the economy (Cheremukhin et al. 2017). Moreover, the growing population and the climate change phenomenon have intensified the concerns over food security among nations (Dawson, Perryman, and Osborne 2016; Cheeseman 2016). This, in turn, has compelled producers to use the resources of this sector, such as the land, water, and biocapacity, at a much faster pace (Legg 2017). This compulsion and subsequent exploitation of resources result in rather inefficient agricultural production, which leads to a substantial degradation of the environment and biodiversity (Gebreselassie, Kirui, and Mirzabaev 2016; Tawe and Neh 2018). Estimates reveal that agricultural production and its input resources management are responsible for around one-fifth of total global GHG emissions (FAO 2020). Though trees, plants, forest land, and water are the sources of CO2 sink, the inefficient and unscientific management of key inputs such as land, soil, fertilizer, energy, and manure often override the CO2 sequestration and sinking while accumulating significant emissions into the environment. Therefore, along with ensuring food security, maintaining sustainability in agriculture production has become a big challenge for countries (Ritchie 2019).

It is evident that geological attributes, geographical elements, and climatic factors have big roles in agricultural production. Certain agricultural production may be suitable in one location but may not suit a different geo-environmental setting. As a result, countries may not always be self-sufficient in the production of all types of food. Furthermore, countries may also lack the capacity (i.e., financial, human capital, infrastructural, and institutional capacity) to improve their technical efficiency and the technological adaptation that would be required to enhance their agricultural production base while adopting a sustainable growth policy in agriculture (Husmann et al. 2015). Technology transfer, knowledge sharing, capacity building, and adequate investment are some of the pivotal factors that may instigate better management and higher efficiency in sustainable agricultural production for countries (Antle, Jones, and Rosenzweig 2017). To facilitate and foster this process, countries have to work more intensely with each other. A regional agreement and cooperation framework can play a significant role in this regard (Binks et al. 2014).

Table 1 identifies the areas of cooperation for efficient agriculture production that can channel efforts into low-emission green growth outcomes in the agriculture sector of various countries. Technology can play a crucial role in determining agricultural productivity. In recent times, the innovation of high-yield crops through advanced applications of agricultural biotechnology, genetic research, and satellite technology has been gaining momentum (Juma 2015). Development, transfer, and sharing of improved technologies, knowledge, and skills within a regional cooperation framework, of course, will enhance the production efficiency of countries as they will achieve more production with proportionately less input (Amanor and Chichava 2016; Emericket al. 2016). Less usage of inputs such as land, fertilizer, machinery, water, and labor will, in turn, reduce environmental damage and emissions. Countries can also develop and share new pro-green growth technologies through mutual financing and institutional support. With improved technology, the cost of production will also be reduced over time. The amount saved from this can be invested in further technology development.

Table 1: Areas of Regional Cooperation, Channels of Impact, and Low-Carbon Growth Goal

Areas of Cooperation	Channel of Impact	Outcome of Low-Carbon Growth
Efficient agricultural production (Technology and knowledge sharing, and capacity building in agricultural production)	Higher yield	Proportionate less use of inputs, lower emissions, and less environmental damage
	Scaling up of production helps to lower the production cost	Additional investment in technology development and adaptation

Source: Author.

For reinforcing an effective green growth policy, it is important to address both of the following issues: maximization of production by using a given level of inputs, and minimization of emissions resulting from the same level of inputs. The first factor relates to production efficiency and the second refers to emission management efficiency. A few papers analyze the role of regional cooperation in agriculture for attaining higher agricultural productivity and food security (Crescenzi, De Filippis, and Pierangeli 2015; Kaur and Kaur 2016; Amanor and Chichava 2016). Much of the contemporary literature highlights the impact of climate change and environmental degradation on agricultural production (Chen, Chen, and Xu 2016; Jat et al. 2016; Zhang, Zhang, and Chen 2017). However, the way in which agricultural production efficiency may eventually impact emissions, environmental degradation, and subsequent climatic change is hardly touched upon. Literature often fails to heed these interlinkages and policymakers rarely suggest using such regional cooperation as a strategic tool to minimize emissions through the channel of agricultural productivity and efficiency improvement. This study examines the role of regional cooperation in achieving sustainable green agriculture through the following two stages:

i. Enhancing the agricultural productivity of countries;

ii. Linking productive efficiency with the reduction of emissions resulting from agricultural activities.

For empirical analysis, countries in all Asian subregions are considered, which include 16 economies in West Asia, 7 in Southeast Asia, 8 in South Asia, 4 in East Asia, and 5 in Central Asia. A list of the countries is presented in **Appendix I.**

Table 2: Statistics on Population, Agriculture Production, and Emissions of Asian Subregions

	Population (2018)		Agricultural Production (2017)		Emissions from Agriculture (2017)		Emission Share to Production Share
Region (Number of countries)	In Millions	Global Share	In Billion USD	Global Share	In Megatons	Global Share	Ratio
Central Asia	72.1	0.9%	17.5	0.7%	76.5	1.4%	2.47
East Asia	1,666.5	21.9%	760.8	30.0%	742.5	13.7%	0.55
South Asia	1,895.8	24.9%	302.1	11.9%	952.3	17.6%	1.78
Southeast Asia	655.3	8.6%	146.2	5.8%	476.0	8.8%	1.84
West Asia	271.0	3.6%	94.6	3.7%	91.2	1.7%	0.54
Asia	4,560.7	59.8%	1,321.1	52.0%	2,338.5	43.2%	1.00

Source: FAOSTAT (2020).

Table 2 reveals that Asia comprises 59.8% of the global population and contributes 52% of global agricultural production. The continent is responsible for 43.2% of global emissions originating from agricultural activities. Since this region, in a global context, has significant implications for agriculture production and its sustainability due to the huge population and economic size, this study found the sample to be a plausible one for this analysis.

Among the subregions, South Asia and East Asia jointly share 46.8% of the global population while producing 41.9% of global agricultural products. In proportion to their productions, their emissions remain relatively low with a combined share of 31.3%. Table 2 also uses an indicator—*Emission Share to Production Share*—to identify the extent of vulnerability in terms of emission generation from agricultural production in a region. If the ratio takes a value over 1, it indicates that the agricultural production of that subregion proportionately emits more than others with a lower ratio. From this, it can be inferred that Central Asia, Southeast Asia, and South Asia tend towards greater emissions from their agricultural activities than West and East Asia.

Agriculture in different parts of the world has different emission intensities, i.e., emission per unit of production. Table 3 shows that agriculture in Europe is the most sustainable in terms of emitting the least from its agricultural production. Europe has the least emission intensity of 1.32 MtCO2-eq/billion USD followed by North America with 1.47 MtCO2-eq/billion USD. Emission intensity is worst in South America with 4.41 MtCO2-eq/billion USD and Africa with 4.20 MtCO2-eq/billion USD. The global average emission intensity in agriculture stands at 2.10 MtCO2-eq/billion USD. In Asia, the West and East Asian regions have the least emission intensity with 0.97 and 0.99 MtCO2-eq/billion USD while Central Asia, Southeast Asia, and South Asia have intensities of 4.09, 3.15, and 3.11, respectively.

Table 3: Emission Intensity, Global Regions (2017)

Area	**Emission Intensity** (Mt C02eq/billion USD)
World	2.10
Africa	4.20
North America	1.47
Central America	2.30
Caribbean	4.15
South America	4.41
Europe	1.32
Oceania	3.84
Asia	1.75
Central Asia	4.09
East Asia	0.99
South Asia	3.11
Southeast Asia	3.15
West Asia	0.97

Source: FAOSTAT (2020).

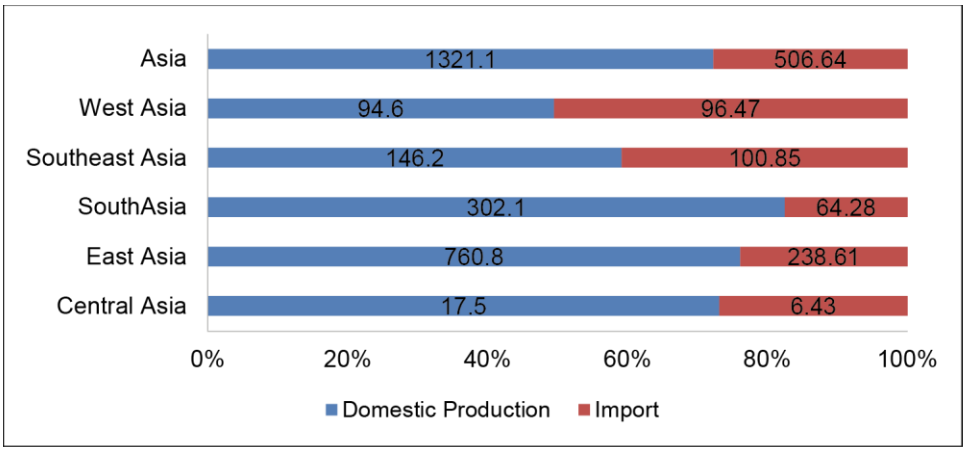
The paper is organized into six sections: Section 2 highlights the recent states of agricultural production and emissions in Asia; Section 3 explains the detailed methodology, model specification, and data; Section 4 interprets the results along with subsequent analysis; Section 5 discusses policy implications of this study; and section 6 ends up with concluding remarks.

2. RECENT STATES OF AGRICULTURAL PRODUCTION AND EMISSIONS IN ASIA

2.1 Inadequate Production to Meet Regional Agricultural Demand

Broadly speaking, Asia remains in a net import position in agriculture, i.e., the import is greater than the export, in aggregate. As Figure 1 illustrates, Asia, in aggregate, has a 38% import dependency (i.e., import divided by production) to meet its agricultural demand. Among the subregions, West Asia has the highest import dependency of 102%, followed by the Southeast Asian countries with 69%. South Asia has the lowest import dependency of 21%.

Figure 1: Agricultural Production and Imports, 2017 (Figures in USD Billion)



Source: FAOSTAT (2020).

Another indicator this study may use is the *Import-to-Export* ratio to signify the extent to which the region can meet the intraregional demand for all agricultural commodities. Table 4shows that East Asia had a net import (i.e., import minus export) amount of USD159.9 billion in 2017. This region is followed by West Asia with USD64.3 billion. Only Southeast Asia has been a net exporting region in Asia with an excess export of USD32.9 billion over its import. The implications are also revealed by the import-to-export ratio.

Table 4: Agriculture Exports and Imports in Asian Subregions (2017)

Region	Net Import (in USD billion)	Import-to-Export Ratio
Central Asia	2.6	1.67
East Asia	159.9	3.03
South Asia	20.2	1.46
Southeast Asia	–32.9	0.75
West Asia	64.3	3.00
Asia	214.1	1.73

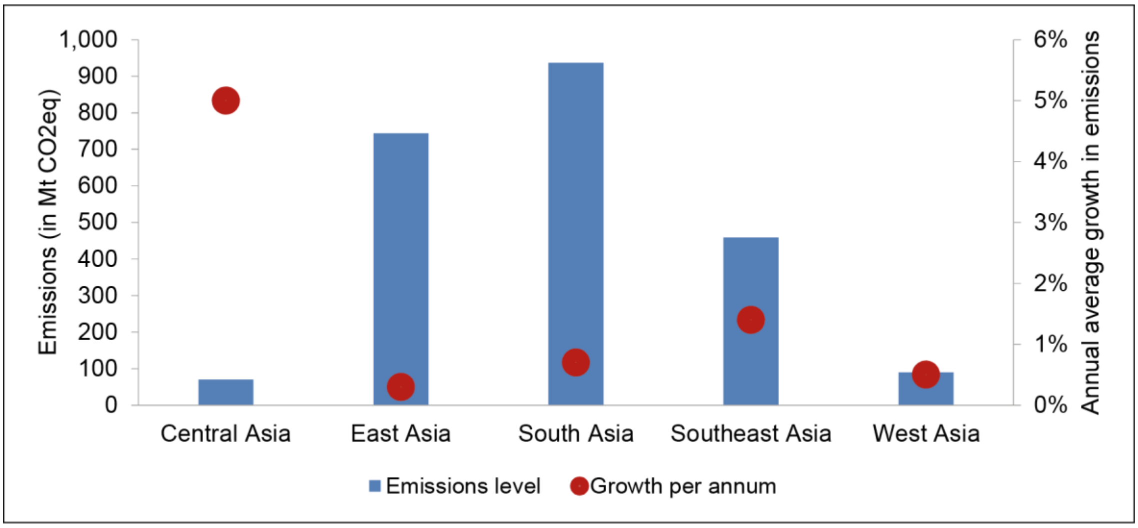
Source: FAOSTAT (2020).

Findings imply that with current settings, the Asian regional blocs are not able to fully meet the intraregional demand for agricultural commodities. However, there are a few signs of potential room for improvement as one region (i.e., Southeast Asia) has an excess supply of agricultural products. However, if the productivity and efficiency of all regions can be improved further with the given level of inputs, production can be increased. Hence, by using economic scale benefits, countries may scale up their production to meet both domestic and regional demands.

2.2 Growing Emission from Agriculture

Figure 2 illustrates the (2013–2017) average levels of emission along with the growth rates during this time in all Asian subregions. Among the regions, South Asia and East Asia emit the highest agricultural production-related emissions with 936.4 and 743.8 megatons CO_2-equivalent. In aggregate, these two regions emit about 73% of Asia's total emissions from agriculture. The growth of emissions from agriculture in Asia is found to be 0.79% per annum over the 2013–2017 period. During this time, the growth was highest in Central Asia with 5.0% per annum. The rate was 1.4% in Southeast Asia while it was lowest in East Asia at 0.3%.

Figure 2: Average Level and Growth Rate of Emissions from Agriculture (2013–2017)



Source: FAOSTAT (2020).

3. METHODOLOGY

From a regional cooperation perspective, we need to estimate the efficiency levels of countries in agriculture production with their current settings. Following the efficiency levels, countries will be able to determine the mechanism of technology sharing and other support to enhance the yield in agriculture production. Moreover, by considering the regional bloc as a common framework, we can estimate the impact of regional cooperation on aggregated production efficiency. Consequently, we can also estimate the untapped potential under a regional cooperation framework.

Several non-parametric methodologies, such as Data Envelopment Analysis, TFPIP, and DPIN, are frequently used in the literature to estimate agricultural productivity and efficiency (Färe et al. 1989; O'Donnell 2010; Khan, Salim, and Bloch2015; Jahromi 2016; Baráth and Fertő 2017). However, nonparametric models often face intrinsic difficulties regarding conceptual and operational issues such as transitivity and identity axioms of index number theory (Matthews2014). An inadequate set of variables and data is another shortcoming of these models in describing the causal relationship.

This paper uses the parametric model stochastic frontier analysis (SFA), which would help not only to calculate production efficiencies but also to show the contributions (elasticities) of the inputs into production efficiency. In recent studies, SFA has frequently been used for measuring production efficiency as well as environmental efficiency at the farm level of agricultural activities (Lansink and Wall 2014; Alves, Moutinho, and Macedo2015; Jiang and Sharp 2015; Orea and Wall 2016; Fei and Lin 2016). However, a combined assessment of production efficiency and emission containment efficiency is not evident. The role of any regional cooperation in balancing and enhancing these efficiencies is also disregarded in the literature. Therefore, this study makes a unique attempt to address all these issues concurrently. The stochastic frontier model is described in the following section in detail.

3.1 Stochastic Frontier Model

Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1977) introduced the concept of a stochastic frontier production function in productivity and efficiency literature. In simple form, the model with panel dataset is expressed as:

$$Y_{it} = \beta X_{it} + (V_{it} - U_{it})$$

$$i = 1,2,3,\dots\dots..,n \text{ and } t = 1,2,3,\dots..,T$$

where,Y_{it} : production (actual value or logarithm value) of the *i*-th firm or country in *t*-th time period

X_{it} :$(k \times 1)$ vector of input values of the *i*-th firm or country in *t*-th time period

β : vector of the estimation parameters

V_{it} : statistical error term, assumed to follow a normal distribution with $N\,(0, {\sigma_V}^2)$ andindependent from U_{it}

$U_{it} = U_i e^{(-\eta(t-T))}$, where U_i refers to nonnegative random variables that capture technical inefficiency of production function; assumed to follow independently and identically distributed as truncated at zero of the $|N\,(\mu, {\sigma_U}^2)|$ distribution

η: a parameter to be estimated

The model requires the use of parameterization by following Battese and Corra (1977) who replace ${\sigma_V}^2$ and ${\sigma_U}^2$ with $\sigma^2 = {\sigma_V}^2 + {\sigma_U}^2$

Parameter γ is then defined as

$$\gamma = \frac{{\sigma_U}^2}{{\sigma_V}^2 + {\sigma_U}^2}$$

The value of γ lies between 0 and 1. It helps towards the iterative maximization process by starting with a suitable value of γ. If the null hypothesis of γ = 0 cannot be rejected, it implies that ${\sigma_U}^2 = 0$. Hence, U_{it}has no implication in the model and therefore can be removed. As a result, the parameters under such conditions can be estimated rather by using the OLS regression technique. Conversely, a higher (closer to 1) and significant value of γ would refer to the validity of using this SFP model.

The imposition of single or multiple restrictions on this model would lead to a few special cases as have appeared in the literature. For example,

- If η =0, the model refers to the time-invariant estimation proposed by Battese, Coelli, and Colby (1989)
- If T=1, the model will be equivalent to the cross-sectional, half-normal distribution as formulated by Aigner, Lovell, and Schmidt (1977)
- If $\mu = 0$, the model will be equivalent to the first model of Pitt and Lee (1981)

Technical efficiency is measured by the SFP model as

$$EFF_{it} = \frac{E(Y_{it}|U_{it}, X_{it})}{E(Y_{it}|U_{it} = 0, X_{it})}$$

In the case of the production function, the value of EFF_{it} lies between 0 and 1.

3.2 Model Specification for Production Efficiency

Two widely applied production functions in SFA are the Cobb-Douglas and translog functions. Each form has its advantages and limitations. The Cobb-Douglas function has been widely used in agriculture economics because of its algebraic tractability while providing a reasonably good approximation of the production function, which usually suits well agriculture production methodology. The main limitation of this Cobb-Douglas form is its restrictive assumptions on arbitrary (i.e., inflexible) substitutability among the inputs. The translog production function overcomes this limitation by allowing *flexible* degrees of substitutability between inputs. However, the key challenge in using the translog function is the high probability of the occurrence of *harmful* collinearity[1] among the explanatory variables as the number of production factors increases (Pavelescu 2011). According to a common translog production function with n number of input factors, the number of estimated parameters equals $\frac{n.(n+3)}{2}$. Hence, a model with five input factors should have 20 estimated parameters. Therefore, it would be difficult to prevent the model from having any collinearity issue. Filippini, Hrovatin, and Zorić (2008), however, suggest dropping the input that has the highest correlation problem with other inputs. A few authors argue that in cases where measuring technical efficiency is the prime objective, multicollinearity problems may be ignored to some extent as the interpretation of the coefficients remains secondary in such circumstances (Puig-Junoy 2001). However, these arguments may not be convincing enough to use the translog function where the probability of collinearity remains higher. Rather, this paper wants to deploy the Cobb-Douglas production function to avoid such complexities. The Cobb-Douglas function may, however, experience a serial correlation problem for time series data and heteroskedasticity

[1] Pavelescu (2010) refers to "harmful" collinearity when the sign of at least one estimated parameter does not match with the relevant sign of the coefficient of the correlation factors between the analyzed variable and the resultative variable.

problems for cross-section data. This paper, however, uses panel data, which would minimize these technical obstacles.

The basic model, shown in Equation (1), is applied for each of the subregions.

Maximizing

$$\ln Output_{i,t} = \beta_0 + \beta_1 \ln Land_{i,t} + \beta_2 \ln Labor_{i,t} + \beta_3 \ln Capital_{i,t} + \beta_4 \ln Fertilizer_{i,t} + \beta_5 \ln Energy_{i,t} - U_{i,t} + V_{i,t} \quad (1)$$

$i = 1, 2, 3, \dots \dots \dots \dots, k$ (for each country)

$t = 1, 2, 3, \dots \dots \dots \dots, T$ (for each year)

Here, *Output* refers to the aggregated agriculture output while *Land* refers to the total arable land of a country, and *Labor* and *Capital* denote the total labor (in number) and capital (in USD) deployed in agriculture. *Fertilizer* and *Energy* refer to the amount of fertilizer and energy consumed in agriculture production. Subscripts *i* and *t* represent the *i*-th country and time, respectively. $U_{i,t}$ denotes the single-sided error term for the combined effects of inefficiency, about which complete information is not available. $V_{i,t}$ refers to the normal statistical error term, which captures the effect of inadvertently omitted variables.

Maximum likelihood estimation (MLE) is used to estimate the coefficients of the model using joint density functions of $U_{i,t}$ and $V_{i,t}$. The parameter γ is found to be significant and implies the best-fit for the model. FRONTIER 4.1 software developed by Coelli (1996) is used to estimate the model.

3.3 Linking Production Efficiency and Emission Reduction Potential

The impact of regional cooperation is estimated by considering each subregion as a unitary bloc. The production efficiency of each country under a bloc is calculated by using the model described in the previous section.

To understand the link between the enhanced production efficiency (to the optimal) and the emission reduction potential, this study uses the following calculation as shown in Table 5.

Table 5: Estimation of the Link between Optimal Production Efficiency and Emission Reduction

Scenario	Input	Output	Emission
Actual scenario	x	y	m
Optimal efficiency in production	x	$[1 + (1 - z\%)] \times y = \epsilon \times y$	m
New level of emission (with current production level and optimal efficiency)	$\frac{x}{\epsilon}$	y	$\frac{m}{\epsilon}$

Now let's assume that a country uses ***x*** unit of aggregated input to produce ***y*** unit of output, which, within the subregional context, estimates the technical production efficiency of that country as ***z%***. This implies that given the existing settings, if the countries within a subregion can work together to remove production barriers and cooperate further to increase its production, the untapped potential production will go up to ***(1-z%)*** without deploying any additional resources (i.e., inputs).

Since the emissions or environmental degradation result from using the inputs in the agriculture production process, let's assume that ***x*** amount of aggregated input leads towards an aggregated emission of ***m***.

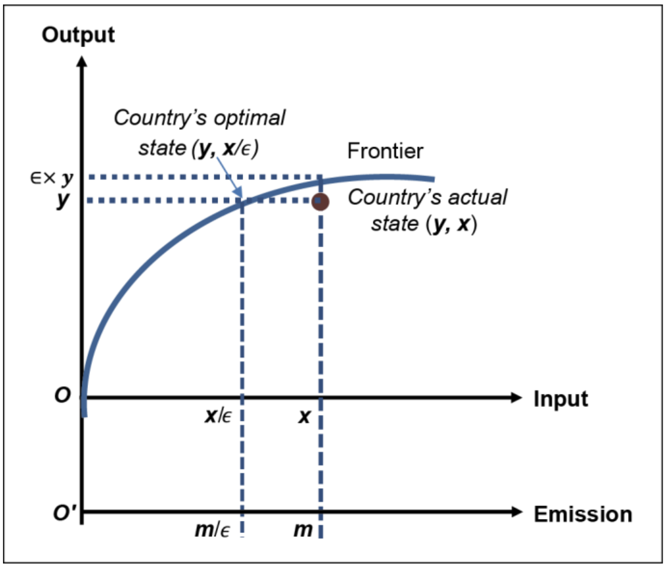
Now with a further increase of efficiency by ***(1-z%)***, ***x*** amount of aggregated input will produce [1+***(1-z%)***]****y*** amount of aggregated output, but the amount of aggregated emission will stay at ***m***. Let's considerϵ = [1+***(1-z%)***] as the optimal efficiency factor. Hence, to produce the agricultural output at the current level (i.e., ***y***) while applying the optimal level of efficiency, the country will now require less input (i.e., ***x/***ϵ), which, in turn, will reduce the emission at the level of ***m/***ϵ.

Hence, the impact factor of emission, θ = ***1/***ϵ

The resultant reduction of emission, $\Delta \boldsymbol{m} = (\boldsymbol{1} - \boldsymbol{\theta}) \times \boldsymbol{m}$

The analysis is also explained in Figure 3.

Figure 3: Estimation of the Link between Optimal Production Efficiency and Emission Reduction



3.4 Rationale for Choosing the Input Variables

Land: Plants, forests, and other natural ecosystems usually play a significant role in carbon sinking and storing. Agricultural activities often encourage the deforestation process by exerting pressure on forest lands and ecosystems (Pant 2009). Therefore, transforming more forests (and other natural ecosystems) into agricultural land would disturb that carbon sinking level and at the same time would emit GHG emissions by burning plant material or farming for the cultivation process. More use of land for agriculture would induce more fermentative processes that would emit CH4. It would also bring more N_2O from soil management and CO_2 from the change in land use (Smith et al. 2014; FAO 2020).

Labor: More labor engaged in a piece of land would indicate more anthropogenic activities and less-scientific cultivation processes applied for agricultural production (Xiong et al. 2016).

Capital: Using more capital machinery may increase the efficacy in production by using advanced technology, yet it would also increase the usage of energy to operate the machinery or technologies. Despite the facilitation of higher production, the probability of emission also remains high with such applications.

Fertilizer: Increased use of nitrogenous and synthetic fertilizer for the production of crops that consume high nitrogen has a severe impact on the increased emission of N_2O (Zhang et al. 2019). Moreover, manure management may also impact the CH4 emission level (Takle and Hofstrand 2015).

Energy: Irrigation, tractor, and harvesting machinery use the consumption of energy in the agriculture process. The use of fossil fuels in these activities is a significant source of agricultural emission (Schneider and Smith 2009; Van Vuuren et al. 2017).

4. DESCRIPTION OF DATA

Data on aggregated agriculture production, arable land, capital, fertilizer, energy consumption in agriculture, and all emissions (in gigagrams) are extracted from the Food and Agriculture Organization (FAO) of the United Nations. Labor data are collected from the *Key Development Indicators* of the Asian Development Bank (ADB) annual reports.

The definition of each variable (as per data sources) is provided here:

Aggregated agricultural production:

Value of gross production is compiled by multiplying gross agricultural productions (comprising cereals, crops—primary and fiber—coarse grain, fruits, livestock, jute fiber, oils, pulses, roots and tubers, tree nuts, and vegetables) in physical terms by respective output prices at the farm gate. Value is expressed in constant 2014 price in million USD.

Arable land:

Arable land consists of land area under temporary crops, meadows, and pastures, and with temporary fallow. It is measured in thousand hectare units.

Capital:

Capital is defined as the consumption of fixed capital (i.e., machinery and other investments) in agriculture, forestry, and fishing. It is calculated in growing stock form over each year and presented at the constant price of 2014 in USD.

Fertilizer:

Fertilizer in agricultural use is primarily comprised of inorganic or chemical nutrients, namely nitrogen (N), phosphorus (P2O5), and potassium (K2O). The unit of this variable is expressed in million tonnes.

Energy:

Direct on-farm agriculture energy use consists of gas/diesel oils, gasoline, liquefied petroleum gas, natural gas, hard coal, residual fuel oil, electricity, diesel oils, etc. It is measured in terajoule energy units.

Labor:

The data measure the active number of laborers engaged in agriculture and forestry as their source of earnings. Labor is measured in thousands in number.

Emission:

Emissions summarize the total greenhouse gas (GHG) generated from agriculture and forest land. The data comprise three key pollutants, namely methane (CH4), nitrous oxide (N2O), and carbon dioxide (CO2) emitted from crop and livestock activities, forest management, and other land usages. It is expressed in megaton CO2-equivalent.

Data are collected for the 2000–2017period for all Asian countries under five subregions as mentioned earlier. The list includes 16 economies in West Asia, 7 countries in Southeast Asia, 8 in South Asia, 4 in East Asia, and 5 in Central Asia. Countries with a lower annual agricultural production of less than USD150 million are not considered.

5. RESULTS AND FINDINGS

5.1 Summary Statistics

Table 6 shows summary statistics of all the input and output factors of the subregions. It states that East Asia, led by the People's Republic of China (PRC), remains the highest-producing subregion with an annual average agriculture production of USD612.7 billion over the 2010–2016 period, which constitutes 48% of Asia's production. South Asia, led by India, follows with 28% of Asia's production. West Asia and Central Asia have the smallest productions in Asia. South Asia covers the highest amount of arable land with 22.1 million hectares while Central Asia has the least with 3.7 million hectares. Around 691 million laborers are engaged in agricultural activities in Asia, of whom 318 million are deployed in South Asia, the highest among all subregions. Conversely, Central Asia has the lowest number of laborers deployed (8.1 million) in agriculture. East Asia invests the highest capital in agriculture production with USD84.8 billion per annum, on average. South Asia has used more fertilizer than any other subregions. East Asia has consumed more than half of the energy that is consumed for agriculture in Asia. In terms of agriculture-related emissions, South Asia emits the highest amount with 929.7 megatons per annum, on average. South Asia is followed by East Asia with 732.8 megatons and Southeast Asia with 453.1 megatons per annum over the 2010–2016 period.

Table 6: Summary Statistics of Input and Output Factors (Annual Average, 2010–2016)

Region	**Production** (in USD billion)	**Arable Land** (in million ha)	**Labor** (in million)	**Capital** (in billion USD)	**Fertilizer** (in million tons)	**Energy** (in petajoules)	**Emission** (in MT)
East Asia	612.7	11.6	247.2	84.8	50.1	1,821.1	732.8
Southeast Asia	196.9	6.9	106.5	22.4	20.6	356.1	453.1
South Asia	359.3	22.1	317.7	33.2	73.9	885.6	929.7
West Asia	67.2	3.8	11.6	13.6	7.9	291.2	88.0
Central Asia	29.4	3.7	8.1	2.8	1.2	129.0	67.5
Asia (aggregated)	**1,265.4**	**48.2**	**691.1**	**156.9**	**153.8**	**3,483.1**	**2,271.2**

Source: Author's calculations based on FAO (2020) and ADB (2020).

5.2 Estimation of the Coefficients

The results of the estimation of coefficients of the production efficiency model for each subregion are presented in Table 7. The estimations are based on 2010–2016 panel data. The results imply that land, capital, and fertilizer have positive implications for a production outcome for all five subregions. The elasticity (i.e., the impact of a 1% increase in input on output) of arable land is highest in South Asia. A 1% increase in arable land would result in a 0.54% increase in agricultural production, *ceteris paribus*. The impact is lower, especially for economies in West Asia and Central Asia. The elasticity of capital machineries found to be highest in Southeast Asia with 0.38, followed by West Asia, East Asia, South Asia, and Central Asia with 0.26, 0.25, 0.15, and 0.06, respectively. The impact of using fertilizer is found to be highest for Central Asian countries with an elasticity of 0.88. The impacts, however, remain mostly lower for other regions. Apart from Central Asia, the impact of the number of laborers deployed in agriculture has positive implications for production. The elasticity is highest for economies in West Asia. The role of energy consumption in agriculture is not very conclusive. West Asia and South Asia have positive impacts while Central Asia has an adverse impact on energy use in agricultural production.

Higher values of gamma (for all subregions) imply that the model is well fitted for explaining the SFA for each subregion.

Table 7: Estimation of Coefficients for Production Efficiency Model

ln(Production)	**West Asia**	**Southeast Asia**	**South Asia**	**East Asia**	**Central Asia**
ln(Land)	0.16*** (0.06)	0.41*** (0.07)	0.54*** (0.10)	0.16 (0.18)	0.15*** (0.03)
ln(Labor)	0.22*** (0.06)	0.20*** (0.08)	0.15** (0.08)	-0.04 (0.11)	-0.06** (0.03)
ln(Capital)	0.26*** (0.05)	0.38*** (0.04)	0.15*** (0.05)	0.25*** (0.04)	0.09*** (0.02)
ln(Fertilizer)	0.06** (0.04)	0.07*** (0.03)	0.09*** (0.02)	0.13*** (0.03)	0.88*** (0.02)
ln(Energy use)	0.06*** (0.02)	0.01 (0.02)	0.07*** (0.03)	0.00 (0.04)	-0.05** (0.02)
Gamma	0.94	0.95	0.92	0.99	0.90
Log-likelihood function	74.65	67.58	77.53	60.40	139.60
LR test	182.68	42.41	83.84	40.34	53.16

Time-in varying (in)efficiency model.

(*** 99% confidence interval, ** 95% confidence interval, *90% confidence interval).

5.3 Estimations of Production Efficiency and Potential Emission Reduction

Table 8 refers to the agricultural production efficiencies and respective potential emission reduction in the West Asian economies under the regional bloc context. Israel has the highest technical efficiency of 95%, followed by the largest producer of this subregion, i.e., Turkey, with 82%. Most of the West Asian economies have lower agricultural production fundamentally due to their landscape and fertility. Georgia, in this subregion, has the least technical efficiency of 27%. In aggregate, the whole subregion has a weighted production efficiency of 70%, which implies that it could increase its production by 30% if all the countries could optimize their production within the existing settings and context. The aggregated impact factor of emission is estimated to be 0.77 for the entire subregion, revealing that at the current production level of the countries but at optimal efficiency, a maximum of 23% of emission (resulting from agriculture) could have been reduced. Considering an annual average (2014–2016) of 89.21 megatons, the potential emission reduction could have amounted to 20.53 megatons per annum in West Asia.

Table 8: Estimation of Production Efficiency and Potential Emission Reduction in West Asia

Economy	**Production Efficiency** (*z*)	**Annual Average Production** (USD mill)	**Untapped Production Efficiency** (1-z)	**Impact Factor on Emission** (θ)	**% of Emission Reduction** (1-θ)	**Emission 2014–2016 Average, MT (m)**	**Emission Reduction in MT** (Δm)
Armenia	43%	1,269.7	0.57	0.64	36%	1.84	0.67
Azerbaijan	44%	2,825.3	0.56	0.64	36%	6.41	2.29
Cyprus	39%	338.8	0.61	0.62	38%	0.37	0.14
Georgia	27%	754.9	0.73	0.58	42%	2.31	0.98
Iraq	46%	2,872.1	0.54	0.65	35%	6.60	2.30
Israel	95%	2,868.5	0.05	0.95	5%	1.47	0.07
Jordan	77%	1,344.9	0.23	0.81	19%	1.17	0.22
Kuwait	44%	339.5	0.56	0.64	36%	0.65	0.23
Lebanon	54%	1,140.7	0.46	0.69	31%	0.77	0.24
Oman	47%	444.0	0.53	0.65	35%	1.51	0.52
Palestine	54%	517.3	0.46	0.68	32%	0.28	0.09
Saudi Arabia	34%	3,415.7	0.66	0.60	40%	5.99	2.38
Syrian Arab Republic	57%	5,803.8	0.43	0.70	30%	6.32	1.91
Turkey	82%	40,785.9	0.18	0.85	15%	44.34	6.83
United Arab Emirates	34%	591.0	0.66	0.60	40%	1.78	0.71
Yemen	32%	1,871.3	0.68	0.60	40%	7.42	3.00
WEST ASIA	**70%**	**67,183.3**	**0.30**	**0.77**	**23%**	**89.21**	**20.53**

Source: Author's calculations.

In aggregate, Southeast Asia has a technical production efficiency of 85%, as shown in Table 9. Malaysia and Thailand have the highest efficiencies with 97% each, followed by the largest producer of this region, Indonesia, with 87%. The Philippines remains the least efficient country in terms of agricultural production in this subregion. Considering the untapped production potential of 15%, the impact factor of emission is estimated to be 0.87. Therefore, with a potential emission reduction of 13%, Southeast Asia could have emitted a maximum of 60.6 megatons CO2-equivalent of agricultural emission per annum by adopting optimal efficiency in agriculture production in the countries.

Table 9: Estimation of Production Efficiency and Potential Emission Reduction in Southeast Asia

Country	Production Efficiency (*z*)	Annual Average Production (USD mill)	Untapped Production Efficiency (1-z)	Impact Factor on Emission (θ)	% of Emission Reduction (1-θ)	Emission 2014–2016 Average, MT (m)	Emission Reduction in MT (Δm)
Cambodia	71%	4,418.7	0.29	0.77	23%	18.55	4.18
Indonesia	87%	66,237.8	0.13	0.88	12%	170.42	20.10
Lao PDR	66%	2,438.3	0.34	0.74	26%	8.36	2.13
Malaysia	97%	15,080.8	0.03	0.97	3%	12.91	0.35
Philippines	62%	22,121.0	0.38	0.72	28%	51.96	14.32
Thailand	97%	34,022.6	0.03	0.97	3%	59.18	1.93
Viet Nam	82%	31,944.5	0.18	0.84	16%	63.57	9.86
SOUTHEAST ASIA	**85%**	**196,861.2**	**0.15**	**0.87**	**13%**	**454.42**	**60.58**

Source: Author's calculations.

South Asia remains one of the most populous regions with a quarter of the global population and about 40% of the global extreme poor population (UNDP 2019). A global agriculture production share of only 12% makes this region relatively more exposed to food security issues. Moreover, the production efficiency of this subregion also remains lower than that of the other subregions, which, importantly, also leads to South Asia emitting the highest agricultural-generated GHGs in Asia. This subregion, in aggregate, has an average weighted production efficiency of 66%, as estimated and presented in Table 10. Bangladesh and Nepal have the highest efficiencies with 98% and 96%, respectively, while Afghanistan and Pakistan have the lowest with 34% and 56%, respectively. With an untapped production efficiency of 34%, this region has an impact factor on emissions of 0.75. Estimates reveal that the entire region could reduce its agriculture-related emissions by up to 235.8 megatons per annum if the countries could produce their agricultural output with optimal efficiency.

Table 10: Estimation of Production Efficiency and Potential Emission Reduction in South Asia

Country	Production Efficiency (*z*)	Annual Average Production (USD mill)	Untapped Production Efficiency (1-z)	Impact Factor on Emission (θ)	% of Emission Reduction (1-θ)	Emission 2014–2016 Average, MT (m)	Emission Reduction in MT (Δm)
Afghanistan	34%	3,626.5	0.66	0.60	40%	14.00	5.57
Bangladesh	98%	22,967.3	0.02	0.98	2%	76.13	1.47
Bhutan	78%	205.6	0.22	0.82	18%	0.46	0.08
India	63%	256,428.5	0.37	0.73	27%	631.79	170.16
Iran	80%	25,867.4	0.20	0.84	16%	30.15	4.93
Nepal	96%	5,949.3	0.04	0.96	4%	21.89	0.79
Pakistan	56%	41,164.1	0.44	0.69	31%	154.12	47.03
Sri Lanka	82%	3,078.0	0.18	0.85	15%	5.51	0.84
SOUTH ASIA	**66%**	**359,286.6**	**0.34**	**0.75**	**25%**	**934.04**	**235.80**

Source: Author's calculations.

East Asia, led by the PRC, has been the highest agricultural producing subregion in Asia. It produces 58% of Asia's agricultural products. However, the agricultural process remains more sustainable as it emits only 31.8% of the agriculture-related emissions in Asia. The technical production efficiency of East Asia remains the highest in Asia with 92%, as depicted in Table 11. The Republic of Korea leads with 97% efficiency followed by the PRC with 93%. The impact factor on emissions is calculated as 0.93, indicating that with the attainment of optimal production efficiency, East Asia could reduce the emission level by 7%, i.e., 54 megatons per annum.

Table 11: Estimation of Production Efficiency and Potential Emission Reduction in East Asia

Country	**Production Efficiency** (*z*)	**Annual Average Production** (USD mill)	**Untapped Production Efficiency** (1-z)	**Impact Factor on Emission** (θ)	**% of Emission Reduction** (1-θ)	**Emission 2014–2016 Average, MT** (m)	**Emission Reduction in MT** (Δm)
PRC	93%	501,265.2	0.07	0.93	7%	682.11	46.35
Japan	74%	18,262.6	0.27	0.79	21%	19.85	4.16
Mongolia	83%	813.5	0.17	0.86	14%	24.01	3.40
Republic of Korea	97%	10,192.9	0.03	0.97	3%	12.71	0.41
EAST ASIA	**92%**	**530,534.2**	**0.08**	**0.93**	**7%**	**738.67**	**54.02**

Source: Author's calculations.

Central Asia has been the lowest agriculture producing subregion in Asia. However, when compared with its production, the rate of emission is relatively higher, as depicted earlier in Table 3. In aggregate, the subregion has a production efficiency of 76%. The Kyrgyz Republic remains the most efficient country with 92% efficiency, followed by Tajikistan with 77% as shown in Table 12. Turkmenistan, conversely, has the least efficiency at 61%. With an untapped production efficiency of 24%, the impact factor on emission (θ)is calculated as 0.81. The subregion could, therefore, reduce 19% of emissions from its current level, which amounts to 13.6 megatons per annum.

Table 12: Estimation of Production Efficiency and Potential Emission Reduction in Central Asia

Country	**Production Efficiency** (*z*)	**Annual Average Production** (USD mill)	**Untapped Production Efficiency** (1-z)	**Impact Factor on Emission** (θ)	**% of Emission Reduction** (1-θ)	**Emission 2014–2016 Average, MT** (m)	**Emission Reduction in MT** (Δm)
Kazakhstan	77%	8,045.7	0.23	0.81	19%	21.48	3.98
Kyrgyz Republic	92%	1,869.4	0.08	0.92	8%	4.66	0.35
Tajikistan	78%	1,434.1	0.22	0.82	18%	5.78	1.04
Turkmenistan	61%	2,675.1	0.39	0.72	28%	8.73	2.44
Uzbekistan	76%	10,749.2	0.24	0.80	20%	29.34	5.75
CENTRAL ASIA	**76%**	**24,773.6**	**0.24**	**0.81**	**19%**	**69.99**	**13.57**

Source: Author's calculations.

Based on the findings and implications, it has been revealed that regional cooperation for optimizing the agricultural production efficiency of countries can be used as an important strategic tool for emission reduction. In the case of Asia, results imply that with concerted efforts under a (sub)regional cooperation framework, an annual emission of GHG in Asia could be reduced by 384.5 megatons CO2eq. This potential reduced amount equals 16.8% of Asia's total emission originating from agricultural activities and 7.1% of that of global emission. If similar efficiency improvement approaches under regional cooperation frameworks could be adopted in other sectors (e.g., industrial, SME, energy, transportation, and service-oriented sectors), there could be a significant reduction of emissions while attaining the current level of production in respective sectors, which would be a pioneering strategic tool en route towards the sustainable development of the region.

6. POLICY IMPLICATIONS

This study should have significant implications in developing a low-carbon agricultural system in a country. From a regional cooperation perspective, a policy framework based on the analysis presented in this paper would provide wide-ranging tools in the transition towards a low-emission agriculture system through improving production efficiency. There should also be other measures to improve emission management in agriculture, but this study provides a different perspective on this solution.

In devising the policies and strategies for subregional cooperation in improving agricultural production efficiencies, broadly two sets of approaches can be adopted based on this study:

a) Estimating the countries' varying capacities in efficiently using different agricultural inputs, and designing a cooperation framework accordingly; and

b) Outlining common set of cooperation tools based on countries' overall strengths and proficiencies.

a) Policies based on productivity of the individual inputs

The productivity of each input is examined to understand the implication and importance of any input for the efficiency of each country. Each of the productivities is calculated as follows:

$$Input\ factor's\ productivity = \frac{Agriculture\ output}{Input\ factor\ usage}$$

Table 13 shows the relative performances of the countries in using their inputs for agricultural production. Though it is assumed that the existing geological, environmental, and spatial factors of the countries largely influence the performances, this ranking gives a general indication of the countries' relative advantages or higher efficiency in using an input (or set of inputs).

From a rational perspective, if a country has a deficiency with any of the endowments or input resources, then it is believed that the country will tend to find out how to increase its efficiency in using that input. The scarcity of the input compels the country to re-engineer or reshuffle the production process so that it can manage to produce more with limited resources. Input substitution may also help this cause for the country. For example, Bangladesh has the lowest per capita arable land within South Asia, which induces it to use the lowest amount of land per unit of agricultural output within that subregion. Similarly, Japan and the Republic of Korea—countries with a dearth of labor—realize the highest labor productivities in the East Asian region.

b) Policies based on a common set of cooperation tools

Technology transfer, knowledge sharing, and capacity-building activities should be facilitated between the high-efficiency countries and the low-efficiency countries so that low-efficiency countries can improve as well (Kiminami and Furuzawa 2013). Institutional settings at the regional level should be strengthened so that they can constantly monitor the level of progress and disseminate adequate policy, rules, and technical support to all member countries. Easing trade restrictions on agricultural production and agricultural inputs may also facilitate efficient production among the countries (Meacham and Rafferty 2016).

Table 13: Ranking in Various Agricultural Productivities (Based on 2010–2016 Average)

Subregion	Rank (1=Best)	Land	Labor	Capital	Fertilizer	Energy
West Asia	1	Kuwait	Israel	Jordan	Yemen	Armenia
	2	UAE	Cyprus	Azerbaijan	Armenia	Iraq
	3	Oman	Jordan	Georgia	Azerbaijan	Palestine
	4	Palestine	Kuwait	Palestine	Oman	Syrian AR
	5	Israel	Syrian AR	Lebanon	Kuwait	Lebanon
	6	Lebanon	Turkey	Oman	Palestine	Oman
	7	Jordan	Oman	Iraq	Israel	Israel
	8	Cyprus	UAE	Syrian AR	Georgia	Yemen
	9	Armenia	Lebanon	Yemen	Cyprus	Turkey
	10	Georgia	KSA	Armenia	Iraq	Kuwait
	11	Turkey	Iraq	Turkey	Turkey	KSA
	12	Yemen	Palestine	Cyprus	UAE	Cyprus
	13	Azerbaijan	Armenia	Israel	Jordan	Jordan
	14	Syrian AR	Yemen	UAE	Syrian AR	Azerbaijan
	15	KSA	Azerbaijan	Kuwait	KSA	Georgia
	16	Iraq	Georgia	KSA	Lebanon	UAE
Southeast Asia	1	Malaysia	Malaysia	Cambodia	Philippines	Lao PDR
	2	Viet Nam	Thailand	Viet Nam	Cambodia	Cambodia
	3	Philippines	Philippines	Lao PDR	Lao PDR	Philippines
	4	Indonesia	Cambodia	Philippines	Thailand	Indonesia
	5	Thailand	Indonesia	Thailand	Viet Nam	Viet Nam
	6	Lao PDR	Viet Nam	Indonesia	Indonesia	Malaysia
	7	Cambodia	Lao PDR	Malaysia	Malaysia	Thailand
South Asia	1	Bangladesh	Iran	Nepal	Bhutan	Sri Lanka
	2	Nepal	Pakistan	Bangladesh	Nepal	Afghanistan
	3	Sri Lanka	Sri Lanka	Bhutan	Afghanistan	Bhutan
	4	Bhutan	Afghanistan	Afghanistan	Iran	Pakistan
	5	Iran	Bhutan	India	Bangladesh	Nepal
	6	India	India	Pakistan	Sri Lanka	Bangladesh
	7	Pakistan	Bangladesh	Iran	Pakistan	India
	8	Afghanistan	Nepal	Sri Lanka	India	Iran
East Asia	1	Rep. of Korea	Japan	PRC	Mongolia	Mongolia
	2	PRC	Rep. of Korea	Mongolia	PRC	PRC
	3	Japan	Mongolia	Rep. of Korea	Rep. of Korea	Japan
	4	Mongolia	PRC	Japan	Japan	Rep. of Korea
Central Asia	1	Uzbekistan	Turkmenistan	Kyrgyz Rep.	Kazakhstan	Kyrgyz Rep.
	2	Tajikistan	Kazakhstan	Uzbekistan	Kyrgyz Rep.	Kazakhstan
	3	Kyrgyz Rep.	Uzbekistan	Tajikistan	Uzbekistan	Turkmenistan
	4	Turkmenistan	Kyrgyz Rep.	Turkmenistan	Tajikistan	Uzbekistan
	5	Kazakhstan	Tajikistan	Kazakhstan	Turkmenistan	Tajikistan

Source: Author's calculations based on FAO (2020) and ADB (2020).

Furthermore, the creation of a common fund to finance agricultural green growth projects may also play an important role. Countries should also focus on cooperating in developing road communication infrastructures to facilitate agriculture, especially in rural areas. Countries should also work together to ensure access to good-quality water in rural areas. Mutual support for workers' capacity building for agriculture is also pivotal.

7. CONCLUSION

The growing population and the climate change phenomenon have compelled producers to undertake faster exploitation of the resources in agriculture production, which also leads towards unsustainable and input-led production growth. The problem is further exacerbated by the increasing emission of GHG from this production process. This paper suggests a solution to this by advocating the role of regional cooperation to increase the technical efficiency level in agricultural production. Concurrently, it links this improvement of production efficiency with emission reduction both theoretically and empirically for all Asian subregions.

This paper first adopts the stochastic frontier model to estimate the efficiency levels of the countries under five subregions in Asia. Following the estimations and other calculations, this study reveals that with concerted efforts under a (sub)regional cooperation framework, an annual emission of GHG in Asia could be reduced by 384.5 megatons CO2eq, which is potentially 16.8% of Asia's total emissions originating from agricultural activities and 7.1% of that of global emissions. Hence it is evident that the strategic tool of regional cooperation would be important for reducing the emissions in agriculture. Reducing emissions by using this efficiency improvement channel may also be adopted for other sectors of the economy.

Nevertheless, the most important issue is framing how effectively countries can formulate the process of regional cooperation. Countries within a regional bloc should design their respective strengths, challenges, and potentials so that they can mutually share all the required knowledge, innovations, expertise, and finance needed to extract the optimal benefit for the region. Agriculture is the key sector for ensuring food security, employment, and poverty alleviation on a larger scale. Hence, policymakers should reinforce its sustainability and growth at the same time. Regional cooperation would, therefore, play that pivotal role in the longer run.

APPENDIX

List of Economies

Subregion	Countries
West Asia (16)	Armenia, Azerbaijan, Cyprus, Georgia, Iraq, Israel, Jordan, Kuwait, Lebanon, Oman, Palestine, Saudi Arabia, Syrian Arab Republic, Turkey, United Arab Emirates, Yemen
Southeast Asia (7)	Cambodia, Indonesia, Lao PDR, Malaysia, the Philippines, Thailand, Viet Nam
South Asia (8)	Afghanistan, Bangladesh, Bhutan, India, Iran, Nepal, Pakistan, Sri Lanka
East Asia (4)	PRC, Japan, Mongolia, Republic of Korea
Central Asia (5)	Kazakhstan, Kyrgyz Republic, Tajikistan, Turkmenistan, Uzbekistan

REFERENCES

ADB. 2020. *Key Development Indicators Data*. Manila: Asian Development Bank.

Aigner, D., K. Lovell, and P. Schmidt. 1977. Formulation and Estimation of Stochastic Frontier Production Function Models. *Journal of Econometrics* 6(1): 21–37.

Alves, M.R., V. Moutinho, and P. Macedo. 2015, May. Economic and Environmental Efficiency in Europe: Evidence from a New Stochastic Frontier Model. In *European Energy Market (EEM), 2015 12th International Conference on the* (pp. 1–4). IEEE.

Amanor, K.S., and S. Chichava. 2016. South–South Cooperation, Agribusiness, and African Agricultural Development: Brazil and China in Ghana and Mozambique. *World Development* 81:13–23.

Antle, J. M., J. W. Jones, and C.E. Rosenzweig. 2017. Next Generation Agricultural System Data, Models and Knowledge Products: Introduction. *Agricultural Systems* 155:186–190.

Baráth, L. and I. Fertő. 2017. Productivity and Convergence in European Agriculture. *The Australian Journal of Agricultural and Resource Economics* 68(1):228–248.

Battese, G.E., and G.S. Corra. 1977. Estimation of a Production Frontier Model: With Application to the Pastoral Zone of Eastern Australia. *Australian Journal of Agricultural and Resource Economics* 21(3):169–179.

Battese, G.E., T.J. Coelli, and T.C. Colby. 1989. Estimation of Frontier Production Functions and the Efficiencies of Indian Farms Using Panel Data from ICRISAT's Village Level Studies. *Journal of Quantitative Economics* 5(2):327–348.

Binks, B., A. Haylen, S. Grimes, and L. Thompson. 2014. *Potential Agricultural Cooperation between Mongolia and Australia*. Department of Agriculture. Australian Bureau of Agricultural and Resource Economics and Sciences.

Cheeseman, J. 2016. Food Security in the Face of Salinity, Drought, Climate Change, and Population Growth. In *Halophytes for Food Security in Dry Lands* (pp. 111–123). Academic Press.

Chen, S., X. Chen, and J. Xu. 2016. Impacts of Climate Change on Agriculture: Evidence from China. *Journal of Environmental Economics and Management* 76:105–124.

Cheremukhin, A., M. Golosov, S. Guriev, and A. Tsyvinski. 2017. The Industrialization and Economic Development of Russia Through the Lens of a Neoclassical Growth Model. *The Review of Economic Studies* 84(2):613–649.

Coelli, T. J. 1996. *A Guide to FRONTIER Version 4.1: A Computer Program for Stochastic Frontier Production and Cost Function Estimation* (Vol. 7, pp. 1–33). CEPA Working papers.

Crescenzi, R., F. De Filippis, and F. Pierangeli. 2015. In Tandem for Cohesion? Synergies and Conflicts Between Regional and Agricultural Policies of the European Union. *Regional Studies* 49(4):681–704.

Dawson, T. P., A. H. Perryman, and T. M. Osborne.2016. Modelling Impacts of Climate Change on Global Food Security. *Climatic Change* 134(3):429–440.

Dun, O., N. Klocker, and L. Head. 2018. Recognising Knowledge Transfers in 'Unskilled' and 'Low-Skilled' International Migration: Insights from Pacific Island Seasonal Workers in Rural Australia. *Asia Pacific Viewpoint* 59(3):276–292.

Emerick, K., A. de Janvry, E. Sadoulet, and M.H. Dar. 2016. Technological Innovations, Downside Risk, and the Modernization of Agriculture. *American Economic Review* 106(6):1537–1561.

FAO. 2020. The Contribution of Agriculture to Greenhouse Gas Emissions. Food and Agriculture Organization. Retrieved from http://www.fao.org/economic/ess/environment/data/emission-shares/en/.

FAOSTAT. 2020. Food and Agriculture Organization of the United Nations website. Available at: http://www.fao.org/faostat/en/#data.

Färe, R., Grosskopf, S., C.K. Lovell, and C. Pasurka. 1989. Multilateral Productivity Comparisons when Some Outputs are Undesirable: A Nonparametric Approach. *The Review of Economics and Statistics* February 1: 90–98.

Fei, R, and B. Lin. 2016. Energy Efficiency and Production Technology Heterogeneity in China's Agricultural Sector: A Meta-Frontier Approach. *Technological Forecasting and Social Change* 109:25–34.

Filippini, M., N. Hrovatin, and J. Zorić. 2008. Cost Efficiency of Slovenian Water Distribution Utilities: An Application of Stochastic Frontier Methods. *Journal of Productivity Analysis* 29(2):169–182.

Gebreselassie, S., O.K. Kirui, and A. Mirzabaev. 2016. Economics of Land Degradation and Improvement in Ethiopia. In *Economics of Land Degradation and Improvement: A Global Assessment for Sustainable Development* (pp. 401–430). Cham: Springer.

Husmann, C., J. von Braun, O. Badiane, Y. Akinbamijo, F.O. Abiodun, and D. Virchow. 2015. Tapping Potentials of Innovation for Food Security and Sustainable Agricultural Growth: An Africa-Wide Perspective. *Available at SSRN 2701830*. Retrieved from https://ageconsearch.umn.edu/record/228855/files/ZEF_WP_144.pdf.

Jahromi, E. R. 2016. Measuring and Analyzing Productivity Growth of Total Factors of Productions for Horticultural Crops by Using Malmquist Index and Data Envelopment Approach (DEA). *Journal of Current Research in Science*. Jan 1(1):814.

Jat, M. L. et al. 2016. Climate Change and Agriculture: Adaptation Strategies and Mitigation Opportunities for Food Security in South Asia and Latin America. In *Advances in Agronomy* (Vol. 137, pp. 127–235). Academic Press.

Jiang, N., and B. Sharp. 2015. Technical Efficiency and Technological Gap of New Zealand Dairy Farms: A Stochastic Meta-Frontier Model. *Journal of Productivity Analysis* 44(1):39–49.

Juma, C. 2015. *The New Harvest: Agricultural Innovation in Africa*. Oxford University Press.

Kaur, S., and H. Kaur. 2016. Climate Change, Food Security, and Water Management in South Asia: Implications for Regional Cooperation. *Emerging Economy Studies* 2(1):1–18.

Khan, F. R. Salim, and H. Bloch. 2015. Nonparametric Estimatesof Productivity and Efficiency Change in Australian Broadacre Agriculture. *Australian Journal of Agricultural and Resource Economics* 59(3):393–411.

Kiminami, L. and S. Furuzawa, S. 2013. Knowledge Creation Through International Cooperation in Agriculture. *Studies in Regional Science* 43(1):79–87.

Lansink, A.O., and A. Wall. 2014. Frontier Models for Evaluating Environmental Efficiency: An Overview. *Economics and Business Letters* 3(1):43–50.

Legg, W. 2017. Green Growth Strategies in Agriculture in OECD Countries. In *Food Security and Sustainability* (pp. 55–70). Palgrave Macmillan, Cham.

Matthews, A., 2015. The Common Agricultural Policy and development. In *Research handbook on EU agriculture law*. Edward Elgar Publishing.

Meacham, C., and J. Rafferty. 2016. *Can Agricultural Cooperation Strengthen U.S.–Cuba Normalization?* Center for Strategic and International Studies. Washington, DC 20036.

Meeusen, W. and J. vanden Broeck. 1977.Efficiency estimation from Cobb–Douglas Production Functions with Composed Error. *International Economic Review* 18(2):435–444.

O'Donnell, C.J. 2010. Measuring and Decomposing Agricultural Productivity and Profitability Change. *The Australian Journal of Agricultural and Resource Economics* 54(4):527–560.

Orea, L. and A. Wall. 2016. Measuring Eco-efficiency Using the Stochastic Frontier Analysis Approach. In *Advances in Efficiency and Productivity* (pp. 275–297). Springer, Cham.

Pant, K. P. 2009. Effects of Agriculture on Climate Change: A Cross Country Study of Factors Affecting Carbon Emissions. *Journal of Agriculture and Environment* 10:84–102.

Pavelescu, F. M. 2010. An Extensive Study on the Disturbances Generated by Collinearity in a Linear Regression Model with Three Explanatory Variables. *Romanian Journal of Economics* 31(2 (40)):65–93.

———. 2011. Some Aspects of the Translog Production Function Estimation. *Romanian Journal of Economics* 32(1):41.

Pitt, M.M., and L.F. Lee. 1981. The Measurement and Sources of Technical Inefficiency in the Indonesian Weaving Industry. *Journal of Development Economics* 9:43–64.

Puig-Junoy, J. 2001. Technical Inefficiency and Public Capital in US States: A Stochastic Frontier Approach. *Journal of Regional Science* 41(1):75–96.

Ritchie, H. 2019. Food Production is Responsible for One-Quarter of the World's Greenhouse Gas Emissions. OurWorldinData.org. Retrieved from https://ourworldindata.org/food-ghg-emissions.

Schneider, U.A. and P. Smith. 2009. Energy Intensities and Greenhouse Gas Emission Mitigation in Global Agriculture. *Energy Efficiency* 2(2):195–206.

Shen, J. and Y. Liu. 2016. Skilled and Less-Skilled Interregional Migration in China: A Comparative Analysis of Spatial Patterns and the Decision to Migrate in 2000–2005. *Habitat International* 57:1–10.

Smith, P. et al. 2014. Agriculture, Forestry and Other Land Use (AFOLU). In *Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* (pp. 811–922). Cambridge University Press.

Takle, E., and D. Hofstrand. 2015. Global Warming: Agriculture's Impact on Greenhouse Gas Emissions. *Ag Decision Maker Newsletter* 12(6):1.

Tawe, T.I. and A.V. Neh. 2018. The Implications of Unsustainable Agricultural Land Resources Exploitation in the Widikum-Menka Highlands, North West Cameroon. *International Journal of Law and Society* 1(1): 34.

UNDP. 2019. *Human Development Reports dataset*. United Nations Development Programme. New York. Retrieved from http://hdr.undp.org/en/content/download-data.

Van Vuuren, D. P. et al. 2017. Energy, Land-Use and Greenhouse Gas Emissions Trajectories Under a Green Growth Paradigm. *Global Environmental Change* 42:237–250.

Xiong, C., D. Yang, F. Xia, and J. Huo. 2016. Changes in Agricultural Carbon Emissions and Factors that Influence Agricultural Carbon Emissions Based on Different Stages in Xinjiang, China. *Scientific Reports* 6:36912.

Zhang, J. H. Shi, H. Tian, X. Wang, J. Zhang, S. Pan, and J. Yang. 2019. Excessive Fertilizer Application Accelerates the Greenhouse Gas Emissions Intensity of Major Croplands in China. *AGUFM* 2019: B13L–2464.

Zhang, P. J. Zhang, and M. Chen. 2017. Economic Impacts of Climate Change on Agriculture: The Importance of Additional Climatic Variables Other Than Temperature and Precipitation. *Journal of Environmental Economics and Management* 83:8–31.