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Agricultural emissions reduction potential by improving technical efficiency in crop production

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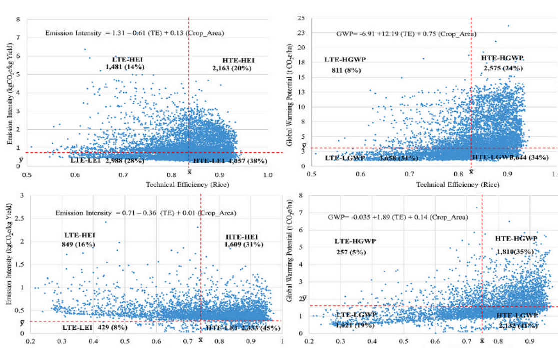
HIGHLIGHTS

- Technical efficiency and GHG emission are influenced by the choice of technologies and management practices
- We used economic and biophysical models to estimate efficiency and GHG emissions reduction from rice and wheat
- Smallholder rice and wheat farmers can reduce emissions by improving technical efficiency and farm productivity

GRAPHICAL ABSTRACT



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ABSTRACT

CONTEXT: Global and national agricultural development policies normally tend to focus more on enhancing farm productivity through technological changes than on better use of existing technologies. The role of improving technical efficiency in greenhouse gas (GHG) emissions reduction from crop production is the least explored area in the agricultural sector. But improving technical efficiency is necessary in the context of the limited availability of existing natural resources (particularly land and water) and the need for GHG emission reduction from the agriculture sector. Technical efficiency gains in the production process are linked with the amount of input used nd the cost of production that determines both economic and environmental gains from the better use of existing technologies.

OBJECTIVE: To assess a relationship between technical efficiency and GHG emissions and test the hypothesis that improving technical efficiency reduces GHG emissions from crop production.

METHODS: This study used input-output data collected from 10,689 rice farms and 5220 wheat farms across India to estimate technical efficiency, global warming potential, and emission intensity (GHG emissions per unit

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of crop production) under the existing crop production practices. The GHG emissions from rice and wheat production were estimated using the CCAFS Mitigation Options Tool (CCAFS-MOT) and the technical efficiency of production was estimated through a stochastic production frontier analysis.
RESULTS AND CONCLUSIONS: Results suggest that improving technical efficiency in crop production can reduce emission intensity but not necessarily total emissions. Moreover, our analysis does not support smallholders tend to be technically less efficient and the emissions per unit of food produced by smallholders can be relatively high. Alarge proportion of smallholders have high technical efficiency, less total GHG emissions, and low emissions intensity. This study indicates the levels of technical efficiency and GHG emission are largely influenced by farming typology, i.e. choice and use of existing technologies and management practices in crop cultivation.
SIGNIFICANCE: This study will help to promote existing improved technologies targeting GHG emissions reduction from the agriculture production systems.

1. Introduction

The reduction of greenhouse gas (GHG) emissions is gradually becoming an important policy objective in global and national agricultural development and food security management. Agricultural production's estimated GHG emissions contribution is 6.2 ± 1.4 gigaton (Gt) CO_2eq y^{-1}, representing ~12% of global anthropogenic GHGs (IPCC, 2019). The land-use change caused by agriculture contributes an additional 4.9 ± 2.5 GtCO_2eq y^{-1} (9%) to global emissions plus GHG emissions from the food supply chain and consumption activities adds up to 37% of the total anthropogenic emission (IPCC, 2019). In absolute terms, the estimated total food system GHG emissions range from 16 to 19 Gt CO_2eq per year globally, depending on the various estimates (Crippa et al., 2021; FAO, 2021). Crop and livestock production alone accounts for a significant proportion (~30% about 5–6 Gt CO_2eq) of all food-related emissions (Poore and Nemecek, 2018). Unless adequately addressed, these emissions are likely to increase as the need for food continues to grow (Ahmed et al., 2020; Mbow et al., 2017). So, agriculture is gradually becoming critical to meeting Paris Agreement's global emissions reduction targets and achieving net-zero emissions, including the Sustainable Development Goals (SDGs).

Globally, food production has significantly increased both by agriculture extensification -expanding cultivation in natural lands (e.g., forest and shrubland) and intensification -improving crop yields in the existing cultivated lands. Lately, agricultural development strategies across the world focus on intensification through the provision of production inputs, including fertilizers, agrochemicals, mechanizations, and irrigation. Agricultural intensification enhanced outputs per unit area that helped avoid a large amount of emissions, which would have been generated through extensification to produce the same amount of production (Burney et al., 2010). These yield gains in crops resulted from the adoption of improved varieties, increased use of agrochemicals and fertilizers, and improved access to irrigation and mechanization. However, the wide-scale adoption of such intensive production practices has also increased GHG emissions from crop production over the years (FAO, 2020).

Major sources of agricultural emissions are nitrous oxide (N_2O) from the use of nitrogenous fertilizer (Reay et al., 2012; Tesfaye et al., 2021; Tian et al., 2020), methane (CH_4) from rice cultivation (Van Groenigen et al., 2013), CH_4 from livestock enteric fermentation and manure management (Caro et al., 2014), and CO_2 from energy consumption in agricultural operations (Gołasa et al., 2021). In addition, agricultural production indirectly drives emissions from the input supply sector, such as fertilizers, agrochemicals, and farm machinery production and transportation. Therefore, improving input use efficiency in food production can substantially contribute to reduction of agricultural emissions (Amelung et al., 2020; Balafoutis et al., 2017; Frank et al., 2016). For instance, the current average nitrogen use efficiency in crop fields across the world is below 40% (Omara et al., 2019), meaning that >60% of applied nitrogen is lost within the soil systems through leaching and/or gaseous forms contributing to the GHG emissions. Reducing the flooding period by using the alternate wetting and drying (AWD) method in rice fields can reduce GHG (CH_4 and N_2O) emissions by up to 40% (Islam et al., 2018).

Although many technologies and management practices are advocated for reducing GHG emissions from crop production (Grewer et al., 2017; Sapkota et al., 2019, 2021; 2022; Tesfaye et al., 2021), there is much debate over the optimal crop production system to achieve the lowest emissions per kg of food grain. Some researchers suggest increasing efficiency in the use of inputs and increasing yields as a means of reducing GHG emissions across the food production systems (Fei and Lin, 2017; Khoshnevisan et al., 2013; Shortall and Barnes, 2013). The technical efficiency of an agriculture farm (production unit) represents its ability to obtain the maximum possible output from a given set of inputs, within the technology level and environmental conditions (Battese, 1992). Accordingly, this study assesses a relationship between technical efficiency and GHG emissions, to test the hypothesis that improving technical efficiency reduces GHG emissions from crop production.

Global and national agricultural development policies normally tend to focus more on enhancing farm productivity through technological change than on the better use of existing technologies. But improving efficiency is necessary in the context of the limited availability of natural resources (particularly land and water) and the need for GHG emission reduction from the agriculture sector (Piñeiro et al., 2020; Ritchie and Roser, 2020). Moreover, productivity improvements are not often entirely attributed to efficiency gains (Ludena, 2010). Efficiency gains in the production process are linked with the amount of input used and the cost of production that determines both economic and environmental gains from the better use of existing technologies. While comparing technical efficiency and GHG emissions, this study presents key factors affecting technical efficiency and how it differs among farm sizes. Good farming practice appropriately combines all inputs necessary to produce a certain level of output with low economic and environmental costs. Poor farming lacks this combination that might generate low technical gains with more environmental impacts.

Globally, about 84% of farms are smallholders with <2 ha of farm area and produce one-third of the world's food (Lowder et al., 2016; Ricciardi et al., 2018). In the majority of low and medium-income countries, particularly in Asia and African regions, >70% of farms are operating <2 ha (HLPE, 2013). Numerous studies argue that smaller farms perform better than larger farms in terms of production, environmental, and socio-economic outcomes (Ricciardi et al., 2021). However, the performance of smallholders in terms of technical efficiency and greenhouse gas emissions remains highly contested. This paper presents estimates of the technical and environmental efficiencies in rice and wheat cultivation under different farm sizes across India. The agricultural sector of India contributes a significant amount of GHG emissions and the country rank 3rd globally in terms of total agricultural emissions (Olivier and Peters, 2017). The latest agriculture census of India shows that small (1–2 ha) and marginal (<1 ha) farmers account for 86% of total farmers in the country (MAFW, 2020). We used the stochastic frontier production function with translog functional form to estimate efficiency in rice and wheat production.

CCAFS' Mitigation Options Tool -CCAFS-MOT (Feliciano et al., 2017) was used to estimate the GHG emissions under the current management practices in rice and wheat cultivation. The tool makes use of several empirical models to estimate GHG emissions, considering all the factors that influence GHG emissions, such as soil, climate, production inputs, and management practices. The latest rice and wheat production-related input and output data from all rice and wheat growing areas released by the Ministry of Agriculture and Farmers Welfare (MAFW), Government of India for 2017–2018 were used for the study. A total of 10,692 and 5222 geo-referenced plot-level data on inputs and crop management represent rice and wheat across India, respectively. We estimated GHG emissions ($tCO_2e\ y^{-1}$), emission intensity (kg CO_2e/kg yield), and technical efficiency for all geo-referenced plot-level data of rice and wheat crops.

2. Data and method

2.1. Data sources

The latest input and output data from India's rice and wheat-growing areas were taken from the cost of cultivation survey (2017) conducted by the Ministry of Agriculture and Farmers Welfare, Government of India (DES, 2017). Of the various information available in this database, field-specific information on tillage, crop establishment and management, including fertilizer and residue management, were taken for estimating the GHG emission. The plot-specific soil data such as texture, soil organic carbon, soil pH, and bulk density were collected from the International Soil Reference and Information Centre database (Hengl et al., 2017). The climate information for the study sites was based on the Koppen Classification System (National Geographic Society). Water management practices for rice in different rice-growing states were taken from Huke and Huke (1997), Bhatia et al. (2013); Gupta et al. (2009). These studies provide information about rice cultivation areas under different water regimes: upland, irrigated, rainfed, and deep-water, and emission coefficients. The location-specific crop duration was obtained from the State Agricultural Departments and commodity research institutes of the Indian Council of Agricultural Research (ICAR).

The input and output data cover 18 rice-growing states and 13 wheat-growing states in India. These states largely differ in terms of climatic conditions, soil type, and crop management practices adopted by rice and wheat-growing farmers. Rice is cultivated in an arid region (e.g. Punjab and Haryana), humid-subtropical (e.g. Uttar Pradesh and Bihar), tropical-wet/dry (e.g. West Bengal, Odisha, and Andra Pradesh) with better access to irrigation and good rainfall during the rice growing season. Wheat is largely cultivated in arid regions (e.g. Punjab, Gujarat, Rajasthan, and Haryana) and humid-subtropical areas (e.g. Uttar Pradesh and Bihar). Wheat is also grown in mid-hill regions where mountain climates exist. Rice and wheat are largely grown in the Indo-Gangetic region where alluvial soil is dominant. A relatively large number of farmers use advanced agronomic practices and agricultural technologies in Punjab, Haryana, and Madhya Pradesh where rice and wheat are dominant crops. A larger proportion of farmers in other regions do not use improved seeds and use less fertilizer, irrigation, and machinery (Agriculture Input Survey 2016–2017 – (MAFW, 2021).

2.2. Estimation of technical efficiency

This study used a stochastic production frontier approach developed by (Aigner et al., 1977) to measure farmers' technical efficiency. In this approach, inputs (land, seed, labor, nitrogen, and irrigation) that farmers have control over were incorporated into the deterministic part of the stochastic production frontier. Management practices such as the use of machinery, irrigation, seed type, tillage practice, and land tenure were included in the inefficiency components of the model. The model can be expressed as:

$$lny_i = lnf(X_{i,}, \beta) + e_i \tag{i}$$

$$e_i = v_i + u_i \tag{ii}$$

$$v_i \sim N[0, \sigma_v^2] \tag{iii}$$

$$u_i \sim N^+(\delta Z_i, \sigma_u{}^2) \tag{iv}$$

Where y_i is the log value of the total output of rice and wheat of the i^{th} farm, X_i is a vector of log of discretionary inputs, β and δ are the unknown parameters to be estimated. The term v_i is a random error with a normal distribution ($v \sim N[0, \sigma_v^2]$) which captures the stochastic effects of factors beyond the farmer's control and statistical noise, and ($u_i \sim N^+(\gamma' Z_i, \sigma_u{}^2)$) is associated with technical inefficiency of production where the technical inefficiency is dependent on Z variables such as irrigation used, seed variety, land tenure, tillage type, and machinery use. u_i is a non-negative random variable that is positive, a half-normally distributed inefficiency variable that measures the technical inefficiency: the gap between actual and potential production given by the frontier.

Eq. (i) does not indicate technical inefficiency factors as it ignores that u is a function of some other variables. Therefore, we follow the single-stage maximum likelihood procedure (Battese and Coelli, 1995) that estimates determinants of technical inefficiency jointly with the other variables of the model. We do not follow a two-stage procedure as it may give inconsistent estimates of the parameters and technical inefficiency, and the results from ordinary least squares in the second stage may not be appropriate because technical inefficiency as a dependent variable is one-sided (Kumbhakar et al., 1991). In this study, we also used a maximum likelihood method to estimate the model, expressed in terms of variance parameters, $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \sigma_u^2/\sigma^2$. The estimated variance parameters were used to calculate farm-specific efficiency. The parameter $\gamma's$ value lies between 0 and 1 and is inversely related to the level of the technical inefficiency. The farm specific technical efficiency is expressed as:

$$TE_i = exp[-E(u_i|e_i)] \tag{v}$$

In general, Cobb-Douglas and translog functional forms are applied for the estimation of the production function. The Cobb-Douglas functional form is the first-order flexible and assumes constant returns to scale. This assumption can be restrictive as one unit increase in input might not increase output by one unit. The translog form is a more flexible form that assumes variable returns to scale. Therefore, Eq. (i) was estimated using the translog functional form to investigate the effects of inputs accounting for agronomic practices and socio-economic factors, expressed as:

$$ln\ Y_i = \beta_0 + \sum_{j=1}^{5} \beta_j ln\ X_{ij} + 0.5 \sum_{j=1}^{5} \sum_{j'=1}^{5} \beta_{jj'} lnX_{ji} lnX_{j'i} + \sum_{k=1}^{5} \times \sum_{j=1}^{5} \beta_{jk} lnX_{ji} lnX_{ki} + v_i - u_i \tag{vi}$$

Where β_{jk} (j, k = 1, …, 5 with j ≤ k) the unknown parameters associated with the explanatory variables in the production function. X_{ij} *(j = 1, …, 5)* represent total land used (ha), total seed (kg), total nitrogen (kg), total labor hours, and total irrigation hours. Inefficiency function u_i in Eq. (iv) and Eq. (vi) is expressed as:

$$u_i = \delta_0 + \delta_1 machinery\ used + \delta_2\ irrigation\ type + \delta_3 seed\ variety + \delta_4 tillage\ type + \delta_5 land\ tenure \tag{vii}$$

We normalized the structural variables (inputs and total production) by their sample mean values before taking their natural logarithms. Therefore, the first-order coefficients can be interpreted as output elasticities evaluated at their sample means. The estimation is carried out using STATA15. Table 1 presents descriptive statistics of variables used in the study.

Table 1
Descriptive statistics of variables used in the study.

Variables	Description
Production	C: Total production (kg)
Land	C: Total crop area (ha)
Seed	C: Total seed used (kg)
Nitrogen	C: Total Nitrogen (kg)
Labour	C: Total labour used (hours)
Irrigation	C: Total irrigation time (hours)
Inefficiency model	
Machine_Use	D: 1 = Machinery used; 0 otherwise
Irrigation_Use	D: 1 = irrigated; 0 otherwise
Seed_Type	D: 1 = improved/ hybrid; 0 otherwise
Tillage_Type	D: 1 = minimum till; 0 otherwise
Land_tenure	D: 1 = leased; 0 otherwise

Note: C: continuous variable; D = dummy variable.

2.3. Estimation of GHG emissions

We used CCAFS' Mitigation Options Tool (CCAFS-MOT) (Feliciano et al., 2017) to estimate the GHG emissions from the current rice and wheat cultivation practices. The tool uses several empirical models to estimate GHG emissions, considering all the factors that influence GHG emissions, such as soil, climate, production inputs, and management practices. The model comprises a generic set of empirical models used to estimate full farm-gate product emissions constituting a mix of Tier 1, Tier 2, and simple Tier 3 approaches. We estimated spatially explicit GHG emissions under current rice and wheat cultivation practices using respective inputs and management data supplemented with soil and climatic data for all 10,692 rice farms and 5222 wheat farms. Field-specific information on tillage and crop establishment, crop management, including water, fertilizer, and residue management as well as grain and biomass yield were considered in the estimation of GHG emissions. The estimation provides total GHG emission per unit area as well as per unit of the product allowing users to estimate the performance of the production system from a GHG emission perspective both in terms of land-use efficiency and efficiency per unit of product. GHG emissions up to the farm gate are reported in CO_2 equivalent (CO_2e) per ha of crops using the 100-year global warming potentials (IPCC, 2014).

3. Results

3.1. Technical efficiency in crop production

Table 2 presents the results of maximum likelihood parameter estimates of a stochastic production frontier analysis for rice and wheat. The deterministic component of the model includes inputs (land area, amount of seed, labor, and nutrient, and irrigation hours) that farmers can control in the production process. The inefficiency component includes factors (i.e. use of machinery, irrigation, seed type, tillage method, and land tenure) that can contribute to reducing the inefficiency in production. The interaction variables and square form of major inputs in the deterministic component represent a non-linear relationship between inputs and outputs in the production function. An increase in crop area, amount of nitrogen use, amount of seed, and irrigation hours have a significant positive impact on rice production.

The production of rice and wheat is negatively related to labor use indicating that labor-intensive rice and wheat cultivation is less productive than replacing labor with machines. This is proved in the inefficiency model where machinery use has -ve value and reduces inefficiency in rice and wheat production. Results show that the interaction effects of various inputs in the production function vary with crops. Interaction of area with another variable (nitrogen, seed, labor, and irrigation inputs) has negative impacts on rice production, but these interaction effects are positive in wheat cultivation, except with labor input. We test the increasing level of nitrogen, seed, labor, and irrigation by using their square value. Results show a positive and significant effect

Table 2
Coefficient estimates of the translog stochastic production function for rice and wheat.

	Rice		Wheat	
Variables	Coefficient	SE	Coefficient	SE
lnArea	0.711***	0.022	0.841***	0.032
lnNitrogen	0.200***	0.010	0.215***	0.011
lnSeed	0.081***	0.012	−0.010	0.029
lnLabour	−0.017*	0.010	−0.022**	0.009
InIrrigation	0.039***	0.006	0.052***	0.007
InArea^2	0.689***	0.076	−1.197***	0.267
lnArea*lnNitrogen	−0.150***	0.026	0.211***	0.049
lnArea*lnSeed	−0.217***	0.029	1.717***	0.228
lnArea*lnLabour	−0.192***	0.033	−0.332***	0.052
lnArea*lnIrrigation	−0.013*	0.008	0.003	0.021
lnNitrogen^2	0.072***	0.014	0.213***	0.018
lnNitrogen*lnSeed	0.062***	0.013	−0.312***	0.044
lnNirogen*lnLabour	0.013	0.011	−0.057***	0.014
lnNitogen*InIrrigation	−0.003	0.004	−0.034***	0.005
lnSeed^2	0.091***	0.016	−1.948***	0.223
lnSeed*lnLabour	0.014	0.013	0.235***	0.045
lnSeed*Inirrigation	0.021***	0.004	−0.017	0.021
lnLabour^2	0.104***	0.018	0.082***	0.019
lnLabour*InIrrigation	−0.005	0.003	0.022***	0.006
lnIrrigation^2	0.032***	0.004	0.031***	0.004
Constant	0.084***	0.014	0.159***	0.007
Inefficiency model				
Machinery_Use	−0.432***	0.062	−0.024	0.067
Irrigation_Use	−0.279***	0.073	−1.332***	0.077
Improved_Seed_Variety	−0.250**	0.098	−0.388***	0.074
Reduced_Tillage	−0.002	0.161	−0.058	0.100
Land_Tenure	−0.263	0.175	−0.089	0.139
Constant	−2.192***	0.128	−0.610***	0.097
Vsigma				
Constant	−2.998***	0.051	−4.220***	0.064
E(sigma_u)	0.237		0.361	
Sigma_v	0.223***	0.006	0.121***	0.004
γ	0.530		0.899	
LLR	−959.52		149.44	
Mean TE	0.830		0.769	
Min TE	0.509		0.214	
Max TE	0.944		0.972	
N	10,692		5222	

Note: Cobb-Douglas (CD) is a restricted functional form that assumes a constant return to scale, so we used a more flexible translog functional form that can capture the non-linear relationship between inputs-outputs. We performed the LR-test to test the null hypothesis that there is no difference between these two functional forms of rice and wheat. The p-value of 0.000 suggests that the translog functional form is a better fit than the CD functional form for both crops. Similarly, the second null hypothesis- there are no inefficiency effects in the model, was tested against the alternative hypothesis that there is an inefficiency effect in the model. The p-value of 0.000 suggests that the inefficiency effect is significant in the model. i.e., the variation in production is due to inefficiency. Finally, the third test was conducted to test if the variables included in the inefficiency model do not affect the level of technical inefficiency. The p-value of 0.000 suggests that the variables included in the inefficiency model affect the technical inefficiency of rice and wheat production in the study area.

of these variables in rice production, only the square value of seed has a negative effect in wheat production. These results show that rice and wheat producers fall under different sections of the production frontiers curve.

This study used translog functional form so that the coefficient value multiplied by 100 represents elasticity. The input elasticities of crop area, nitrogen, seeds, and irrigation were 71%, 20%, 8%, and 4%, respectively. The negative input elasticity of labor in rice (−2%) indicates that increasing shares of household labor employed in agriculture result in lower productivity per unit labour use and thus lower efficiency. The average technical efficiency in rice production is 0.83 (range 0.51–0.94), which suggests a scope to improve efficiency in rice production by 0.17. Our analysis shows that >40% of rice plots have technical efficiencies below average. The use of machinery, irrigation, and improved seed variety can significantly decrease the inefficiency (i.e. improve technical efficiency) in rice production in the sampled rice farms. Machinery has the largest impact on reducing inefficiencies in rice production followed by irrigation and improved seeds. Farmers who cultivated rice on rented field reduced the inefficiency compared to farmers cultivating on their own land. Mechanization and level of input use (fertilizer, water, and improved seeds) were high in the rented plots.

An increase in plot size (i.e. crop area), amount of nitrogen use, and irrigation hours have a significant positive impact on the stochastic production frontier of wheat too. The input elasticities of crop area, nitrogen, and irrigation were 81%, 21.5%, and 5.2%, respectively. The negative input elasticities of the amount of seed (−1%) and labor use (2.2%) indicate more seed and labor use would contribute negatively to wheat yield. The average technical efficiency in wheat production is 0.77, suggesting a scope to improve efficiency in wheat production by 0.23. About 25% of wheat farmers have technical efficiencies below average. Irrigation has a large impact on reducing inefficiencies in wheat production, followed by improved seeds. The use of machinery and reduced tillage can improve technical efficiency, but this effect is insignificant. Farmers renting land for rice and wheat cultivation were more efficient than farmers cultivating in own land.

Table 3 summarises the technical efficiency of rice and wheat-growing states across the country. The technical efficiency of rice production in Uttarakhand, Karnataka, Andra Pradesh, and Punjab is higher than in other rice-growing states in India. Similarly, the technical efficiency of wheat production in Haryana, Punjab, Rajasthan, and Madhya Pradesh is higher than in other wheat-growing states in India. This variation is largely affected by the level of technology adoption (improved seed, irrigation, fertilizer, and mechanization) and improved agronomic practices (tillage, sowing, weed control, and pest management). Farmers in some states, such as Haryana and Punjab, are highly advanced in the adoption of modern agricultural technologies and practices in rice and wheat cultivation.

Table 3
Summary of technical efficiency for rice and wheat growing states in India.

State (Rice Growing)	N	Mean Technical Efficiently (SD)	State (Wheat Growing)	N	Mean Technical Efficiently (SD)
Andhra Pradesh	879	0.865 (0.055)	Bihar	1052	0.771 (0.102)
Assam	408	0.826 (0.078)	Chhattisgarh	25	0.521 (0.116)
Bihar	999	0.788 (0.050)	Gujarat	411	0.704 (0.145)
Chhattisgarh	409	0.798 (0.088)	Haryana	318	0.850 (0.083)
Gujarat	426	0.840 (0.065)	Himachal Pradesh	276	0.575 (0.124)
Haryana	183	0.849 (0.050)	Jharkhand	51	0.661 (0.124)
Himachal Pradesh	97	0.838 (0.074)	Karnataka	31	0.681 (0.237)
Jharkhand	533	0.778 (0.070)	Madhya Pradesh	450	0.791 (0.129)
Karnataka	74	0.867 (0.050)	Maharashtra	169	0.660 (0.194)
Kerala	491	0.826 (0.080)	Punjab	575	0.839 (0.085)
Madhya Pradesh	168	0.751 (0.086)	Rajasthan	540	0.809 (0.126)
Maharashtra	168	0.737 (0.086)	Uttar Pradesh	1247	0.780 (0.109)
Odisha	1903	0.843 (0.051)	Uttarakhand	70	0.740 (0.215)
Punjab	521	0.862 (0.047)			
Tamil Nadu	640	0.863 (0.047)			
Uttar Pradesh	803	0.807 (0.054)			
Uttarakhand	38	0.870 (0.042)			
West Bengal	1952	0.845 (0.058)			

*SD represents Standard Deviation.

3.2. Technical efficiency and GHG emissions

Fig. 1 presents the distribution of rice and wheat farms in four quadrants- 1st: Low Technical Efficiency-High Emission Intensity or High Global Warming Potential (LTE-HEI or LTE-HGWP), 2nd: Low Technical Efficiency-Low Emission Intensity or Low Global Warming Potential (LTE-LEI or LTE-LGWP), 3rd: High Technical Efficiency-Low Emission Intensity or Low Global Warming Potential (HTE-LEI or HTE-LGWP), and 4th High Technical Efficiency-High Emission Intensity or High Global Warming Potential (HTE-HEI or THE-HGWP). A large proportion of farms has high technical efficiency and low emissions intensity (TE $>\overline{x}$ and EI $<\overline{y}$) in the rice (39%) and wheat (43%). Low global warming potential with high technical efficiency was found in 46% rice and 40% wheat plots. These are the most desirable conditions from the economic and environmental aspects of crop production. Interestingly, relatively low proportions of rice and wheat farmers fell in the 1st quadrant: low technical efficiency and high emission intensity (11% in rice and 16% in wheat), and low technical efficiency and high global warming potential (4% in rice and 5% in wheat). These are the least desirable conditions from the economic and environmental aspects of crop production.

*2020More than30% of farmers in rice production and 8% of farmers in wheat production have low technical efficiency with low emissions intensity (TE $<\overline{x}$ and EI $<\overline{y}$). Similarly, about 23% of farmers in rice production and 20% in wheat production have low technical efficiency with low global warming potential (TE $<\overline{x}$ and LGWP $<\overline{y}$). These conditions are environmentally desirable but can be economically inefficient. These farms can contribute to maximizing crop outputs through the use of existing technologies and management practices. This is also important for the regions where food insecurity is a growing issue. Farmers in the 3rd quadrant are particularly important for targeting emissions reduction under technically efficient conditions. More than 19% of farmers in rice production and 32% of farmers in wheat production have high technical efficiency with high emissions intensity (TE $>\overline{x}$ and EI $>\overline{y}$). About 28% of farmers in rice production and 35% of farmers in wheat production have high technical efficiency with high global warming potential (TE $>\overline{x}$ and LGWP $>\overline{y}$). For these categories of farmers, the use of current technologies and management practices is helping to maximize outputs but not minimizing the environmental footprint of rice and wheat production.

Results show that there is a negative relationship between technical efficiency and emission intensity, and a positive relationship between technical efficiency and global warming potential (see equation in each panel). These relationships indicate that an increase in technical efficiency can decrease emission intensity but may increase total global warming potential in rice and wheat production. It was observed that yield maximization with a combination of existing technologies and management practices can decrease emissions intensity by closing yield gaps, but the use of inputs (e.g., fertilizer, machinery, and irrigation) to minimize inefficiency can increase total emissions per unit of land area. However, increased emissions through intensification can be offset by avoiding the emissions elsewhere that would have occurred due to the cultivation of more land to produce same amount of food.

3.3. Farm size, technical efficiency, and GHG emissions

Table 4 presents the distribution of rice and wheat fields by farm size, technical efficiency, and GHG emissions. A large proportion of smallholders (<1 ha crop area) represent high technical efficiency and low

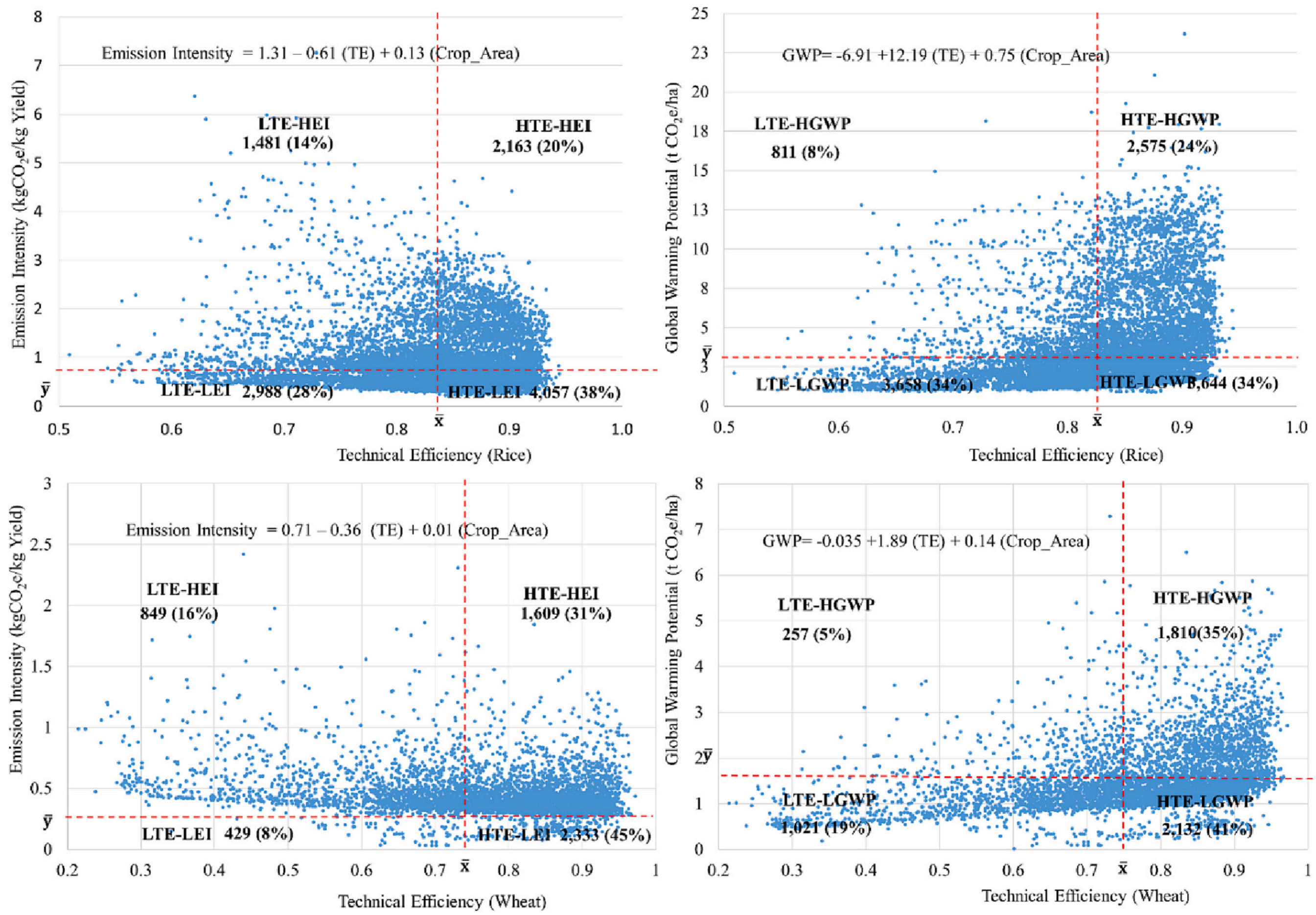

Fig. 1. Level of Technical Efficiency (TE), Emission Intensity (EI)) and Global Warming Potential (GWP) in rice and wheat cultivation. Quadrant 1: LTE-LEI (Low Technical Efficiency-Low Emission Intensity), Quadrant t 2: HTE-LEI (High Technical Efficiency-Low Emission Intensity), Quadrant 3: HTE-HEI (High Technical Efficiency-High Emission Intensity), and Quadrant 4: LTE-HEI (Low Technical Efficiency-High Emission Intensity). $\overline{x}$ and $\overline{y}$ represent average TE and EI or GWP among the survey farms, respectively. The number of farms and their % in total surveyed households are presented in each quadrant. The average TE in rice and wheat was 0.83 and 0.70. Average EI and GWP in rice was 0.96 $kgCO_2e/Mg$ yield and 3.8 tCo_2e/ha, and in wheat was 0.4 $kgCO_2e/Mg$ yield and 1.5 tCo_2e/ha. Equations in the 1st and 3rd panels represent a relationship of EI with TE and crop area, and equations in the 2nd and 4th panels represent a relationship of GWP with TE and crop area.

emission intensity (HTE-LEI: 41% in rice and 46% in wheat) and high technical efficiency and low global warming potential (HTE-LGWP: 51% in rice and 46% in wheat) compared to the large landholders (>1 ha crop area). The proportion of smallholders and largeholders in low technical efficiency and high emission intensity (LTE-HEI) and low technical efficiency and high global warming potential (LTE-HGWP) is very low compared to other categories of TE and GHG emissions, and not significantly different between farm sizes. But significant differences in TE and GHG emissions were observed between the farm size in HTE-HEI and HTE-HGWP. Despite high technical efficiency, large landholders have high emission intensity and global warming potential in both rice and wheat cultivation.

This analysis shows that any farm size can generate low to high TE, EI, and GWP, and fall in any quadrant (in Fig. 1) based on farming practice. Rather, the choice of technologies, level of input use, and management practices have a significant role in determining TE and GHG emissions at the farm level. The use of the appropriate combination of technologies and management practices (i.e., Good Farming Practices) is helping to improve TE and reduce GHG emissions in all farm sizes. Low technical efficiency and high GHG emissions were also observed in all farm sizes under the inappropriate use of available technologies and management practices (i.e., Poor Farming Practices).

4. Discussion

4.1. Improving technical efficiency vs. technological change

A large proportion of rice and wheat farmers in India are technically inefficient, and this indicates the potential to increase yields if inefficiencies in rice and wheat production are reduced or eliminated. Results also show that improving technical efficiency in crop production can reduce GHG emissions intensity. Technical efficiency plays a large role in closing the yield gaps by optimal use of production inputs (i.e. seeds, water, and fertilizer) and enhancing productivity per unit of land. This relationship between technical efficiency and emission intensity is in line with the prevailing scientific studies conducted in the crop and livestock sub-sectors (Dong et al., 2018; Gerber et al., 2013; Henderson et al., 2016). Global data on emission intensity by crops over time also shows a decreasing trend in emission intensity with improved technical efficiencies in crop production and yields (FAO, 2020). The main determinants of reducing emissions intensity in crop production are efficient use of nitrogen fertilizers and mechanization (Mrówczyńska-Kamińska et al., 2021). These results suggest that the agricultural development program that targets reducing emissions intensity can focus on improving technical efficiency.

The overarching goal of agriculture development is to increase food production while also reducing GHG emissions, if possible,without

Table 4
Technical efficiency, emission intensity, and GWP by farm size.

Technical Efficiency	Emission Intensity and GWP	Rice		Wheat	
		Farm size <1 ha	Farm size= >1 ha	Farm size <1 ha	Farm size = >1 ha
High-TE	Low-EI	3,358 (41%)	824 (33%)	1569 (46%)	698 (39%)
High-TE	High-EI	1,290 (16%)	752 (30%)	1032 (30%)	646 (36%)
Low-TE	Low-EI	2,599 (32%)	652 (26%)	269 (8%)	162 (9%)
Low-TE	High-EI	939 (11%)	283 (11%)	576 (17%)	276 (16%)
High-TE	Low-GWP	4,138 (51%)	741 (30%)	1592 (46%)	541 (30%)
High-TE	High-GWP	1,175 (14%)	1,197 (48%)	1009 (29%)	803 (45%)
Low-TE	Low-GWP	1,977 (24%)	450 (18%)	679 (20%)	345 (19%)
Low-TE	High-GWP	294 (4%)	123 (5%)	166 (5%)	94 (5%)
Total		8,185	2,508	3,443	1,780

	Good farming		Transition		Poor farming

Note: The cut-off point for farm size was chosen for 1 ha based on the average farm size in India (1.08 ha in 2015–2016). About 70% of farmers in India are operating below 1 ha holding size (Agriculture Census of India 2015–16). **Good Farming** represents a good combination of inputs applied based on crop requirements to maximize outputs that give low emission intensity and/or low global warming potential, **Poor Farming** indicates the inappropriate combination of inputs for crop production that can't maximize outputs and generates high global warming potential (and/or high emission intensity), **Transition** represents farms that either couldn't get high TE or low emission intensity/low GWP under the current technologies and crop management practices.

compromising its primary objective of food production. Emission reduction goal is gradually becoming important to meet the global emission reduction targets (Richards et al., 2018; Wollenberg et al., 2016). But our analysis shows that improving efficiency of existing technologies and management practices in crop production reduce emission intensity but does not reduce total emissions per unit of land area. This is becasue increase in technical efficiency is directly linked to the use of production inputs (fertilizers water, and machinery) that not only increase crop yield but also contribute to increasing GHG emissions. However, looking from the global perspective, increasing yield by improving technical efficiency may reduce or avoid emissions elsewhere due to non-requirement of additional land to produce the same amount of food.

Many recent studies advocate nutrients, water, and energy management technologies and practices that can contribute to increasing yields and reducing GHG emissions from crop production (Ilahi et al., 2019; Maaz et al., 2021; Sapkota et al., 2017; Zoli et al., 2021). In many locations, excess nitrogen use for crop production contributes to a large amount of GHG emissions (Tesfaye et al., 2021). This excess nitrogen-induced N_2O emission can be substantially reduced by using site-specific nutrient management practices without compromising yield reduction (Aryal et al., 2019; Sapkota et al., 2021). Reduction in water use for crop production, particularly in flooded rice cultivation, reduces GHG emissions (CH_4) by 30–70% without yield loss (Allen and Sander, 2019; Richards and Sander, 2014). Shifting from fossil fuel energy to alternative energy in farm operations significantly contributes to emissions reduction from agriculture (Acosta-Silva et al., 2019; Ashok et al., 2021). Thus, improving technical efficiency and adopting new technologies and management practices can be a strategy to achieve the overarching goal of increasing food production as well as climate action.

4.2. Farm size vs. farming typology

Some studies argue that opportunities for smallholders to reduce emissions might come from improving their technical efficiency in crop production (Clark and Tilman, 2016; Cohn et al., 2017). This is particularly important where a large number of farmers are smallholders, and they account for a large proportion of food produced and supplied in the market, for example, in South Asia and sub-Saharan Africa. But our analysis does not support the hypothesis that smallholders tend to be technically less efficient and the emissions per unit of food produced by smallholders can be relatively high. A large proportion of smallholders in our study have high technical efficiency, low emissions intensity, and low GHG emissions per unit area. Another result from our analysis shows large landholders with high technical efficiency have high GHG emissions (tCO_2e/ha) primarily driven by high degree of mechanization, frequent irrigation and more fertilizer application. The argument that smallholder farming systems are often GHG-intensive relative to other production systems might be context-specific. More importantly, in all farm sizes, better nutrient and soil management, tillage, and irrigation practices can help increase crop yields and generate mitigation co-benefits (Milder et al., 2011; Vermeulen et al., 2012).

4.3. Climate-smart agriculture and technical efficiency

Technologies and practices discussed in sections 4.1 and 4.2 that help increase crop yields and generate GHG mitigation co-benefits are largely considered climate-smart agriculture technologies and practices. A broad range of climate-smart agriculture includes the use of improved seeds, water, nutrient, and soil management technologies and practices (Aryal et al., 2020; Khatri-Chhetri et al., 2019) that also contribute to increasing technical efficiency in crop production (Ho and Shimada, 2019; Pangapanga-Phiri and Mungatana, 2021). Some recent studies conducted in the Indian sub-continent region show a large potential for those climate-smart agricultural technologies and practices in reducing GHG emissions (e.g., Kakraliya et al., 2021; Sapkota et al., 2017). Therefore, the adoption of climate-smart agricultural technologies and practices in rice and wheat production systems generates multiple benefits: enhance farm productivity, increase technical efficiency, and reducing GHG emissions in many smallholder farming systems.

5. Conclusion

This study demonstrates the use of technical efficiency measurement in identifying GHG emissions hotspots by farm size and farming practices, and assessing the potential adoption of mitigation measures in agriculture. We hypothesized that the agricultural GHG emissions (both total emissions per ha and emission intensity per kg of crop production) are influenced by technical efficiency via farm size and farming practices. Results support our hypothesis that technical efficiency significantly varied among the farm size, which is also reflected in quantities of GHG emissions. This study indicates a large potential for GHG emissions reduction from the smallholder farming systems by improving technical efficiency as well as farm productivity.

Moreover, our analysis indicates that any farm size could be technically efficient and reduce GHG emissions by choosing a combination of good farming practices. Levels of technical efficiency and GHG emission are largely influenced by farming typology, i.e. choice and use of existing technologies and management practices in crop cultivation. Our analysis also indicates that the technical inefficiency can largely be reduced by using farm machinery (for tillage and intercultural operation, and harvesting), irrigation, and improved seeds. Therefore, policies targeting agricultural GHG emissions reduction should consider intervention measures that are linked to farm mechanization, water, nutrient, and seed management.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request to the corresponding authors.

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