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Pathways and determinants of sustainable energy use for rice farms in India

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ABSTRACT

Rice cultivation in the Northwestern Indo-Gangetic Plains (IGP) of India is often associated with high energy use, calling into question its sustainability. We applied a bootstrapped meta-frontier with a truncated regression to a database of 3,832 rice farms from the input-intensive rice production tracts of the Northwestern IGP as part of an assessment of energy use efficiency aimed at identifying entrypoints for more sustainable and efficient practices. District-specific technical efficiency score ranged between 0.68 and 0.99, with a mean of 0.86–0.90, suggesting an average potential for improvement in energy use efficiency of 10–14% within each district. Observed mean meta-frontier technical efficiency scores ranged between 0.60 and 0.81. On average, energy use efficient farms had 42% or higher energy use efficiency in the districts of Ambala, Fatehgarh Sahib, and Karnal. In contrast, in other districts efficient farms had 5-19% higher energy use efficiency than the inefficient farms. Higher rates of tillage, irrigation, and fertilizer application were identified among inefficient farms, with patterns of energy use efficiency varying to some extent between study districts. Both efficient and inefficient farms in Kapurthala and Ludhiana exhibited similar patterns of energy for tillage and land preparation, whereas the energy output from both efficient and inefficient farms were similar in Kurukshetra. These data suggest that in order to improve the efficiency of energy use in rice farms in the Northwestern IGP, district-level policy interventions and incentives might be required. The methodological approach and evidence provided in this study may be of use to identify pathways toward sustainable energy use in other intensively managed rice production landscapes in other countries. Similar analyses that employ meta-frontier and truncated regression approaches can be carried out for other performance indicators, for example profitability and carbon footprints, to explore and identify management and policy interventions to assist farmers to more appropriately utilize scarce and costly resources.

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1. Introduction

List of abbreviations including units and nomenclature

CSISA	Cereal System Initiative for South Asia
CCAFS	CGIAR research program on Climate Change, Agriculture and Food Security
CIMMYT	International Maize and Wheat Improvement Center
CRS	Constant Returns to Scale
DEA	Data Envelopment Analysis
DMU	Decision Making Unit
E_I	Energy input (MJ ha^{-1})
E_o	Energy output (MJ ha^{-1})
EUE	Energy use efficiency
IGP	Indo-Gangetic Plains
IQR	Inter Quartile Range
ME score	Meta efficiency score
MTR	Meta technology ratio
ODK	Open Data Kit
TE score	Technical efficiency score
VRS	Variable Returns to Scale

Power of pump unit used: HP, 1 HP = 746 W
Depth of water table unit used: Feet, 1 feet = 0.3048 m
EUE, TE score, ME score, and MTR are dimension less
All energy input and output in MJ ha^{-1}

Rice plays a critical role in maintaining food security in India, accounting for over a quarter of the country's total calorie intake [1]. The Green Revolution of the 1960s transformed India's rice production landscape through the adoption of high yielding varieties, greater input use, and the expansion of irrigation and mechanization [2,3]. However, rice cultivation is an energy-intensive process, requiring greater inputs compared to other cereal crops. This is due to the intensive puddling and tillage practices in rice paddies, as well as the higher use of agrochemicals [4]. The energy inputs for rice production come from various sources, including diesel-powered tractors for preparatory tillage and puddling, diesel or electric pumps for irrigation, and the use of fertilizers. On average, 6.4 MJ of energy is required to produce 1.0 kg of rice, with the majority of energy input attributed to irrigation and fertilizer use [5,6].

In the North-western Indo-Gangetic Plain (IGP) of India, long standing policies of providing highly subsidized nitrogen fertilizer and electricity for irrigation to farmers has incentivized the excessive use of fertilizer and water for rice production. However, these additional inputs do not always result in a corresponding increase in yield [7,8]. Such excessive resource use not only results in low resource use efficiency and high carbon footprint [33,51], but also creates multiple environmental sustainability issues. In the past, increased rice production was achieved through energy-intensive methods, relying heavily on electricity and diesel consumption. The production, transportation, and application of inputs also require energy and carbon from non-renewable sources [9]. As India faces an energy crisis from non-renewable sectors, the need for sustainable energy use has become imperative to fulfil energy demands without rapidly depleting non-renewable resources. Agriculture, as a sector, transforms energy inputs such as fertilizers, agrochemicals, machinery, diesel, electricity, and manpower into nutritive energy sources through photosynthesis. Hence, energy inputs in agriculture cannot be avoided and the level of input affects the energy output. On farm decisions around the amount and timing of energy inputs vary greatly based on knowledge, technology availability, perceived benefits, and prevailing biophysical conditions, in turn affecting energy output in the form of rice yield and contributing to highly heterogenous energy use efficiency in the region. . Increased energy use may not always be economically viable, and it can also increase the carbon footprint of farming [8]. A recent study in the Gangetic Plains of India indicates that the energy use efficiency of cereal crops, including rice, is decreasing [10]. TDesigning a pathway for judicious use of energy in rice production is the need of hour, given the huge demand for energy by other non-agricultural sectors and activities and importance for the sustainability of future rice production.

An inventory of the energy use associated with key management practices like tillage, irrigation, fertilizer application, labor, and agrochemicals; and energy output in rice grain yield is required to compute the energy use efficiency and to estimate its variability among farms. Although numerous studies estimated the energy use efficiency for rice-wheat cropping systems in Northwestern India [11], only few compared and classified farms as efficient and less efficient and identified the key drivers affecting energy use efficiency [5,6]. Singh et al. [5] concluded energy use efficiency for rice production in Western Punjab was in the range of 0.94–0.97 and that ca. 2200 MJ ha^{-1} could be saved with efficient crop management. The latter was also observed in Karnataka where energy use can be reduced by 6% in puddled transplanted conditions [6]. Yet, the aforementioned studies relied on a limited number of observations and hence, do not capture well the diversity of input-output combinations observed across farms and tend to overestimate the energy use efficiency scores derived from Data Envelopment analysis (DEA) [12]. Thus, our study is novel in employing the bootstrapped meta frontier approach using DEA to classify farms as efficient and less efficient from the inventory of energy use and using a truncated regression to find the drivers of energy use efficiency across a large number of farms. The farm level inventory of energy use pattern is important for policy planning in this region, as the farms in the IGP rely on external inputs. This study can guide policy planners on targeting inefficient farm clusters and operations. DEA is a benchmarking technique, which provides an efficiency score indicating the extent to which a farm is efficient relative to its most energy efficient peers (i.e., farms producing a given level of output with the least possible energy)[6,13,14]. The use of DEA invites erroneous estimates of efficiency scores if outliers are present near the boundary of the frontier. Therefore, bootstrapped DEA was applied in this study as such approach does not rely on single most boundary points.

The present study was designed to i) assess the main sources of energy use for rice cultivation and estimate energy input, output, and hence efficiency, ii) benchmark energy use efficiency against the most energy use efficient farms observed in the sample while identifying options to reduce energy input without compromising energy output, i.e., designing a sustainable energy use pathway for rice farms and, iii) identify the determinants of energy use efficiency in the intensive rice production systems in the Northwestern IGP of India. It was hypothesized that farmers spend additional energy in most of the field operations like tillage, irrigation, fertilizer, and labor, which can be reduced without compromising energy output. Such study at the regional level involved the analysis of 3,832 fields from 7 different districts and contributes to better understand the sustainability of rice cultivation in India with respect to energy use.

2. Material and methods

2.1. Survey data collection

Agronomic management and socio-economic data referring to the 2020–2021 rainy season (*Kharif* rice) were collected from 3,832 farmers' fields located in the Haryana and Punjab states of India. The districts and villages were purposively selected to represent the level of intensification, technology adoption, and access to extension services in the region. Farms within each village were randomly selected from the voter list. All surveyed fields were geo-referenced and the number of

surveyed farms per district is presented in Fig. 1. A structured questionnaire (see Appendix 1) was prepared to include the key variables affecting rice crop productivity and needed to characterize the socio-demographic situation of each farm. The questionnaire was tested before the actual survey and was implemented with an Android smart phone-based Open Data Kit: ODK application survey by trained enumerators. In about 25% of the surveyed fields, the research team determined the grain and straw yield by manually harvesting the crop from 2×2 m^2 randomly selected quadrants besides recording farmers' self-reported yield, whereas, in the remaining 75% of the sample, only the self-reported yield from the largest plot was recorded [7]. After data collection, the ODK forms were uploaded to the Cereal System Initiative for South Asia (CSISA) server by the enumerators.

2.2. Data processing

A web-based dashboard was developed to visualize the data uploaded to the CSISA server and to identify potential errors during data collection. Real-time error checking was done with the help of univariate statistical methods like boxplot and histogram and enumerators were requested to revalidate outliers. Upon completion of data collection, univariate outlier screening for rice yield, fertilizer application, and number of irrigations was done per variety using the Inter Quartile Range (IQR) (boxplot technique). Quartile 1–1.5 x IQR was considered the lower threshold and Quartile 3 + 1.5 x IQR was considered the upper threshold. Bivariate outliers were identified using the robust *Mahalanobis distance* [15] and such cases were not used in the analyses. Further details about the survey and outlier screening are provided in Nayak et al. [7].

Expert knowledge was used to correct data requested on labor use. To do so, the relationship between different variables was considered while examining the outliers in data, e.g., labor use for fertilizer application depends on the amount of fertilizer applied, labor cost of transplanting depends on labor man-days used for transplanting. The time required to apply mineral fertilizers was estimated based on the reported fertilizer amount and the assumption that average laborers take 1.4 hr to apply a 50 kg fertilizer bag manually and at the same time a 50 kg fertilizer bag can be applied in 1 hr if laborers are most efficient and a maximum of 2.2 hr if they are not efficient. Moreover, it was checked if the reported application times were between the minimum and maximum application times calculated and if not, such values were replaced with the nearest minimum or maximum application time. When family laborers were used for transplanting, the reported labor use by farmers was generally small and thus replaced by a minimum of 7-man days of labor used for transplanting. Similarly, maximum labor use for transplanting was fixed at 25 man-days.

2.3. Computation of energy input, energy output, and energy use efficiency

The main sources of energy input were selected based on the management practices reported by rice farms in Punjab and Haryana. The latter included inputs such as mineral fertilizers, electricity for irrigation, diesel for tillage operations, agrochemicals, manual labor, and seeds. Farmers used electricity mainly for pumping groundwater used in irrigation and diesel in field operations involving machinery. Standard coefficients were retrieved from the literature (Table 1) to estimate the energy input associated with the use and manufacturing of mineral fertilizers and other agrochemicals. The energy input of mineral fertilizers and other agrochemicals was then calculated by multiplying the physical units of each input recorded in each field with coefficients retrieved from the literature. For the machinery involved in the tillage operations, the time required to complete land preparation at one go, the diesel consumption per hour, and the number of operations as reported by farmers were used to calculate the energy input associated with tillage operations. The energy input associated with the use of machinery was calculated as follows:

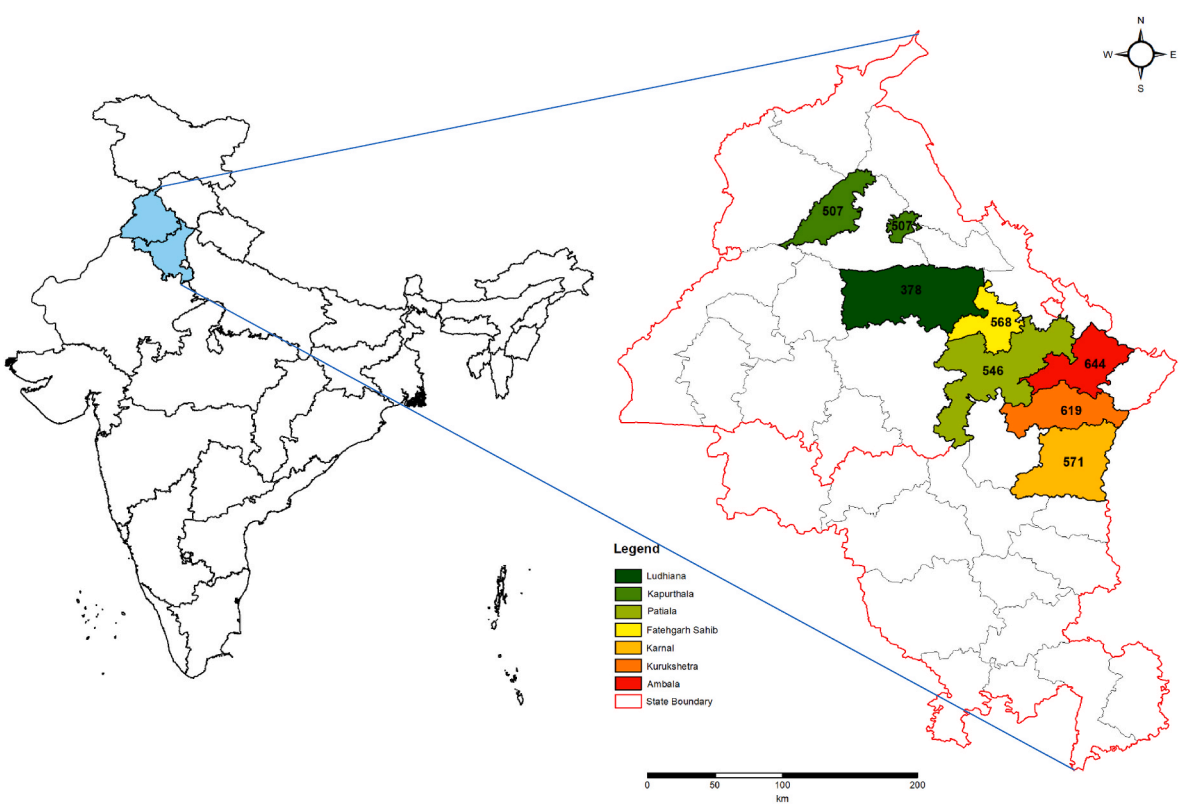

Fig. 1. Location and number of surveyed rice fields in the states of Punjab and Haryana in the Indo-Gangetic Plains of India.

Table 1
Energy equivalent coefficients used to estimate energy input for rice farms in the Northwestern Indo-Gangetic Plains of India.

Variables	Energy equivalent (MJ unit^{-1})
Manual labor (hour)	1.96
Diesel (L)	56.31
Fertilizer Nitrogen (kg)	60.60
Fertilizer P_2O_5 (kg)	11.10
Fertilizer K_2O (kg)	6.70
Fertilizer Zinc (kg)	20.90
Herbicide (kg)	254.40
Insecticide (kg)	184.60
Fungicide (kg)	184.60
Electricity (kW h^{-1})	11.93
Rice grain (kg)	14.70

References: [18, 42], Fertilizer P_2O_5: Phosphorus fertilizer, Fertilizer K_2O: Potassic fertilizer.

$$Energy\ input\ from\ tillage = \sum Ei \tag{1}$$

$$Ei = \sum\Big(Number\ of\ hrs\ required\ for\ field\ preparation\ per\ ha \times Diesel\ consumption\ per\ hr \times Number\ of\ times\ specific\ machinery\ was\ used \times Energy\ coefficient\ of\ diesel\Big) \tag{2}$$

where *Ei* is the energy used in tillage operation *i*. Suppose three tillage implements were used, then diesel consumption was computed for each machinery based on the time required for field preparation, which were further summed to get the total energy use in field preparation. Although the energy equivalent coefficients were available in the literature [16], the time required to prepare a one ha field and the associated diesel consumption were used as per the data in Table 2. The latter refers to a standard working depth and were estimated in the Central Soil Salinity Research Institute (CSSRI), Karnal, India. The energy consumed during manufacturing the machinery was not considered in the calculation of energy input.

Electricity is the main source of energy used for irrigation in the Northwestern IGP of India, and it is heavily subsidized by the government in the region. However, for the purpose of this study, the exact energy expenditure for irrigation was computed. For the computation of electricity requirements for irrigation, a secondary survey was conducted to gather further information about irrigation management in which farmers were asked through a scheduled questionnaire the information related to the power of the pumps used, the depth of the water table, and the number of hours taken to irrigate a field of one ha (i.e., the time for complete irrigation) among others. This secondary survey comprised a sample size of 582 farms representing all the blocks of the districts which are the next tier administrative sub-units of a district. The secondary survey was carried out across all these blocks for irrigation pumps for their power outputs and irrigation durations. A median value of the pumping power outputs (HP) and irrigation durations (in h) were assumed representative across a block and used to calculate electricity consumption of a single field unit according to Kashyap and Agarwal [17],:

$$Electricity\ consumption\ (kW\ hr) = Time\ required\ for\ single\ irrigation\ (hr) \times Number\ of\ irrigations \times Power\ of\ pump\ (HP) \times 0.75 \tag{3}$$

The total labor required (in hours) for irrigation was assumed the same as the duration of irrigation. Correspondingly, the labor used for irrigation was added with other labor use for seedbed preparation, sowing, fertilizer and pesticide application, harvesting, and threshing. Finally, the total energy input was calculated as the sum of energy inputs from tillage operations, irrigation, mineral fertilizer, agrochemicals, and total labor use (Equation (4)). The energy input for harvesting through a combine harvester was excluded from the calculation of energy input and energy use efficiency because it was constant across all the farms cultivating non-basmati rice. Energy input, energy output, and energy use efficiency (EUE) were calculated as follows:

$$\text{Energy input}\ \left(E_I;\ \text{MJ ha}^{-1}\right) = \sum_{i=1}^{n}(I_1 + I_2 + \ldots + I_n) \tag{4}$$

$$\text{Energy output}\ \left(Eo;\ \text{MJ ha}^{-1}\right) = \text{rice yield}\ \left(\text{kg ha}^{-1}\right) \times energy\ coefficient\ (E_C) \tag{5}$$

$$\text{EUE (MJ/MJ)} = E_o\ /\ E_I \tag{6}$$

where, I_1, I_2, …, I_n, refer to the energy input involved in the manufacturing and application of fertilizers and pesticides, the energy used for tillage operations and irrigation, and total labor use.

Table 2
Diesel consumption per hour and time required to complete land preparation for 1 ha as measured for the standard working depth of the machinery in the Central Soil Salinity Research Institute-Karnal.

Tillage implements	Diesel consumption (L hr^{-1})	Time for land preparation (hr ha^{-1})
Harrow	8.18	1.59
Planker	4.55	1.05
Tiller	7.82	1.22
Wet harrow	10.00	2.37
Rotavator	11.27	2.37

2.4. Energy use efficiency analysis: A double bootstrapped meta-frontier approach

Energy use efficiency (EUE) is defined here as the ratio between the energy obtained in the useful output (e.g., crop yield) and the energy input used during the crop production process (Equation (6) [14,18]). A farm is considered energy use efficient if it produces the maximum energy output (*i.e.,* rice yield) with the least possible energy input used in production process [19]. Energy use efficient farms are defined as those leading to a "best-practice frontier" of energy use efficiency but may not essentially form a "production frontier" [20]. If a farm's actual production is lower than the frontier yield (i.e., it lies beneath the frontier), then this farm is considered energy inefficient. In contrast, if a farm's actual production is identical to the frontier yield (i.e., the farm lies on the frontier), then this farm is most efficient with respect to energy use [21]. The estimation of the energy use efficiency frontier is crucial in understanding pathways to minimize the energy input for the production of output in agriculture. Conversely, estimating a single frontier for the entire sample of farms within a given region assumes that all farms operate under a similar biophysical environment and have similar expertise, technology, and market accessibility. Thus, there is a high chance of a false interpretation of varying energy use efficiency at the farm level due to heterogeneity in the production environment (Supplementary Tables 1A and B). To overcome the above, EUE estimation based on a meta-frontier approach can be employed using either the parametric stochastic frontier analysis or the non-parametric data envelopment analysis (DEA). The latter was used in this study.

The DEA meta-frontier approach [22–24] involves estimating the frontier at local or group level (here district) with distinct biophysical environment and technology accessibility and estimating a global frontier (meta-frontier) with the pooled energy input–output data set of all the sample of rice farms surveyed (n = 3832), without any biophysical or technology differentiation. By taking two hypothetical regions as an example, Fig. 2 illustrates the concept of meta-frontier technical efficiency as the input-output efficiency with respect to the energy that provides the robust estimation of EUE. Assuming that the

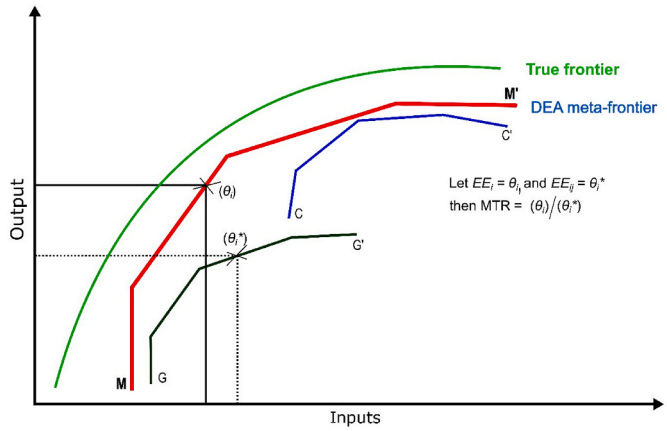

Fig. 2. Meta-frontier approach depicting the true frontier, the bootstrapped data envelopment analysis (DEA) meta frontier (MM'), and the group wise frontier (GG' and CC'). The reader is referred to the main text for further explanation of the figure. Source: Modified by authors after Aravindakshan et al. (2018).

two regions are biophysically heterogeneous, and/or operate at different technology levels, would result in entirely different EUE frontiers for the two regions. Let the EUE frontiers of the groups be C, C′, and G, G' (Fig. 2). The technology gap of the *i*th farm is represented by the distance between θ_i and θ_i*, where θ_i represents the global meta-frontier and θ_i* represents the local or district specific frontier for *i*th farm's EUE. The ratio between the θ_i and θ_i* is called meta technology ratio (MTR), with reference to EUE. The M, M′ in Fig. 2 represents the global meta frontier (Fig. 2). Generally, the point estimate of EUE is produced by DEA models, which are often deterministic in nature. Simar and Wilson [25] showed that the technical efficiency scores of a standard DEA are serially correlated and biased. Hence Simar and Wilson [26] introduced the procedure of smoothing and bootstrapping. The same was used in this study to estimate bias-corrected EUE efficiency scores and confidence intervals around them.

2.4.1. Step 1: Group frontiers with biophysical and technological heterogeneity

Let us assume a sample of '*n*' farms (each farm is a decision-making unit; DMU, converting inputs into output) functioning in one of the seven study districts. Further, the *i*th farm (DMU_i) in district '*j*', produces '*m*' outputs ($y_{ij}...y_{mj}$) using '*k*' energy inputs ($x_{ij}...x_{kj}$) and the observed rice production data (crop yield) represents an unbiased approximation for the true rice production output (crop yield) of the respective *i*th farm. In general, EUE is represented by θ, the ratio between the weighted sum of energy outputs and the weighted sum of energy inputs. For optimization of EUE, a vector of weights for energy input and output are assigned to each of the farms. Let ($k \times n$) input matrix "X" and ($m \times n$) output matrix "Y" represent the weighted sums of input and output vectors for all the surveyed farms and each farm belongs to one of seven different districts *j*. In the present study, k = 5 inputs (i.e., energy use in tillage operations, fertilizer, agrochemicals, irrigation water, and manual labor) and m = 1 output (energy output from rice grain yield; Equation (5)) are input-output parameters for the DEA model. The R package "Benchmarking" was used for fitting the DEA model [27].

The standard DEA model proposed by Charnes et al. [28], often referred to as the Charnes, Cooper, and Rhodes (CCR) model, is the basis of the meta-frontier estimation. The CCR input-oriented model for the *i*th farm in the *j*th district is defined as follows:

$$Min_{\theta_{ij}}\theta, \text{ and } j = 1, 2, \ldots, 7 \tag{7}$$

subject to:

$$-y_{ij} + Y\lambda \geq 0 \; \theta_{x_{ij}} - X\lambda \geq 0$$

where θ is the EUE score for farm *i* in district *j*, and λ is an n × 1 weights vector corresponding to peer weights. For the *i*th farm of the *j*th district, these are represented by the vectors x_{ij} and y_{ij}, respectively. The EUE scores (θ) are computed by restricting the energy output to input ratio between 0 and 1. Further to maximize θ, the weights are assigned to the energy inputs and outputs, such that the *j*th districts' EUE is obtained by solving Equation (7).

The CCR input-oriented model (Equation (7)) assumes constant return to scale (CRS), i.e., the ratio between the change in outputs to change in inputs is constant. If with successive addition of inputs, the farm produces less and less output, the farm can be categorized as operating under variable returns to scale (VRS), which is assumed to be the case for rice production in the Northwestern IGP of India [7].

The VRS assumption refers to (a) an increasing return to scale, i.e., if output increases by more than the proportional change in all inputs or (b) a decreasing return to scale, i.e., if an increase in inputs leads to less than proportional increase in output [21]. In the case of crop production, often the relationship between input and output follows the diminishing rate of marginal return or variable return to scale (decreasing return) [19,21]. Thus, an additional constraint pertaining to convexity ($\lambda \leq 1$; see Equation (8)) was added to the CCR model to capture VRS, which then is called the Banker, Charnes and Cooper (BCC) model [29]:

$$EUE_{ij} = \underset{\theta_{ij}^{VRS}\lambda}{Min}\theta_{ij}^{VRS} \; subject\ to\ Y_{ij} \leq Y\lambda; \theta_{ij}^{VRS}X_{ij} \geq X\lambda; \geq 0, given \sum_{j=1}^{n}\lambda_{ij} = 1 \tag{8}$$

where *Y* represents the energy output vector and *X* represents the energy input vector, respectively, and θ_{ij}^{VRS} is the EUE score of the *i*th farm in the *j*th district under VRS. For any district *j*, the average EUE score ranges between $0 \leq \theta_j^{VRS} \leq 1$. However, θ_j^{VRS} equals 1 when all the farms lie perfectly on the production frontier, and all the farms are thus energy use efficient. Although the "total" or "overall" technical efficiency is distinguished from "pure" technical efficiency (Equation (8)) [30], the $1\text{-}\theta_i^{VRS}$ value represents the inefficiency measure (the distance between the efficiency frontier to the current efficiency level) for the *i*th farm. The smoothed bootstrap procedure was employed on θ_j^{VRS} to generate the bias-corrected district-specific technical efficiency scores '$\bar{\bar{\theta}}_i$' (TE scores) [26]. The district-specific TE scores indicate how efficient is the DMU's with respect to the peers of the same districts. So, a high mean district-specific TE score with small standard deviation indicates the farms in a particular district are homogenous with respect to energy input and output.

2.4.2. Step 2: Approximation for global meta-frontier

Specified that the farms in the respective districts of the study area use different crop management practices under different biophysical conditions, then the global meta-frontier encompasses input-output combinations of the seven districts surveyed (Fig. 2). Further, the conceptual illustration shows that the estimation procedure used here is based on a piece-wise linear frontier for both the global meta-frontier and the district-specific frontiers (Equations (9) and (10)). As explained in step 1 of the DEA model, the same technique can simply be applied to all surveyed farms by pooling the observations. Thus, for all the farms in different districts the deterministic meta-frontier DEA model can be stated as follows (see Equation (8) for an explanation of the abbreviations used):

$$EUE_i = \underset{\theta_i^{VRS}\lambda}{Min}\theta_i^{VRS} \; subject\ to\ Y_i \leq Y\lambda; \theta_i^{VRS}X_i \geq X\lambda; \lambda \geq 0, given \sum_{i=1}^{n}\lambda_i = 1 \tag{9}$$

In Eq. (9), a bootstrap procedure was employed to generate the bias-corrected meta-frontier efficiency scores ($\bar{\bar{\theta}}i^*$, ME scores). The meta-technology ratio (MTR) is presented as the distance between the district-specific frontier and the global meta-frontier. The MTR is calculated as the ratio of obtained output for the *j*th district, relative to the potential output defined by the meta-frontier given the observed level of energy input [23]. The MTR thus captures energy use efficiency differences between the meta-frontier encompassing the pooled sample and the respective district-specific frontier, and is expressed as:

$$\mathrm{MTR} = \frac{\bar{\bar{\theta}}_i}{\overset{*}{\theta}_i =} \tag{10}$$

The MTR indicates the scope of energy use efficiency improvement (ME scores) of the farms for a specific district and it reflects the distance between the meta-frontier and the district-specific efficiency frontier. As an illustration, a comparatively small average MTR for a specific district indicates a large output gap between the meta-frontier and the farm in the respective group.

2.4.3. Step 3: Bootstrapped truncated regression

In step 3, the determinants of energy use efficiency of rice farming in the studied districts were investigated using a bootstrapped truncated regression [31], which was estimated as follows:

$$\bar{\bar{\theta}}_i = {}^{i}a + Z_i\delta + \varepsilon_i, i = 1, \ldots, n \tag{11}$$

where $\bar{\bar{\theta}}_i$ are the bias-corrected estimates of DEA energy use efficiency scores from the district-specific frontier analysis (TE scores), $\varepsilon_i \sim N(0, \sigma_\varepsilon^2)$ with right-truncation at $1 - Zi\delta$; a is a constant term, and Zi is a vector of explanatory variables. We included in the bootstrapped truncated regression of the efficiency scores agronomic factors like delay in sowing beyond 132nd Julian days (10th of May), crop duration, the timing of 1st and 2nd urea top-dress application, scaled herbicide, fungicide and insecticide used (kg active ingredient kg^{-1} of formulation) and soil texture. Socioeconomic factors like age of the household head, landholding size, and family size were also included. The variable water table depth was also used as a regressor. The bootstrap truncated regression was estimated using the "*truncreg*" package in R [32].

Farms were classified as most and least efficient based on the bias-corrected ME scores ($\bar{\bar{\theta}}i^*$; Equation (9)) to gain insights on how farms in each district perform with respect to energy management. Farms with a ME score in the top 20% percentile of ME scores were classified as most efficient farms whereas farms with a ME score in the bottom 20% percentiles of ME scores were classified as least efficient farms. A non-parametric Wilcox-test was used to test whether the mean energy input per operation, total energy input, and total energy output differed between the most and least energy efficient farms. Electricity use for irrigation accounted for a large share of the total energy input as it

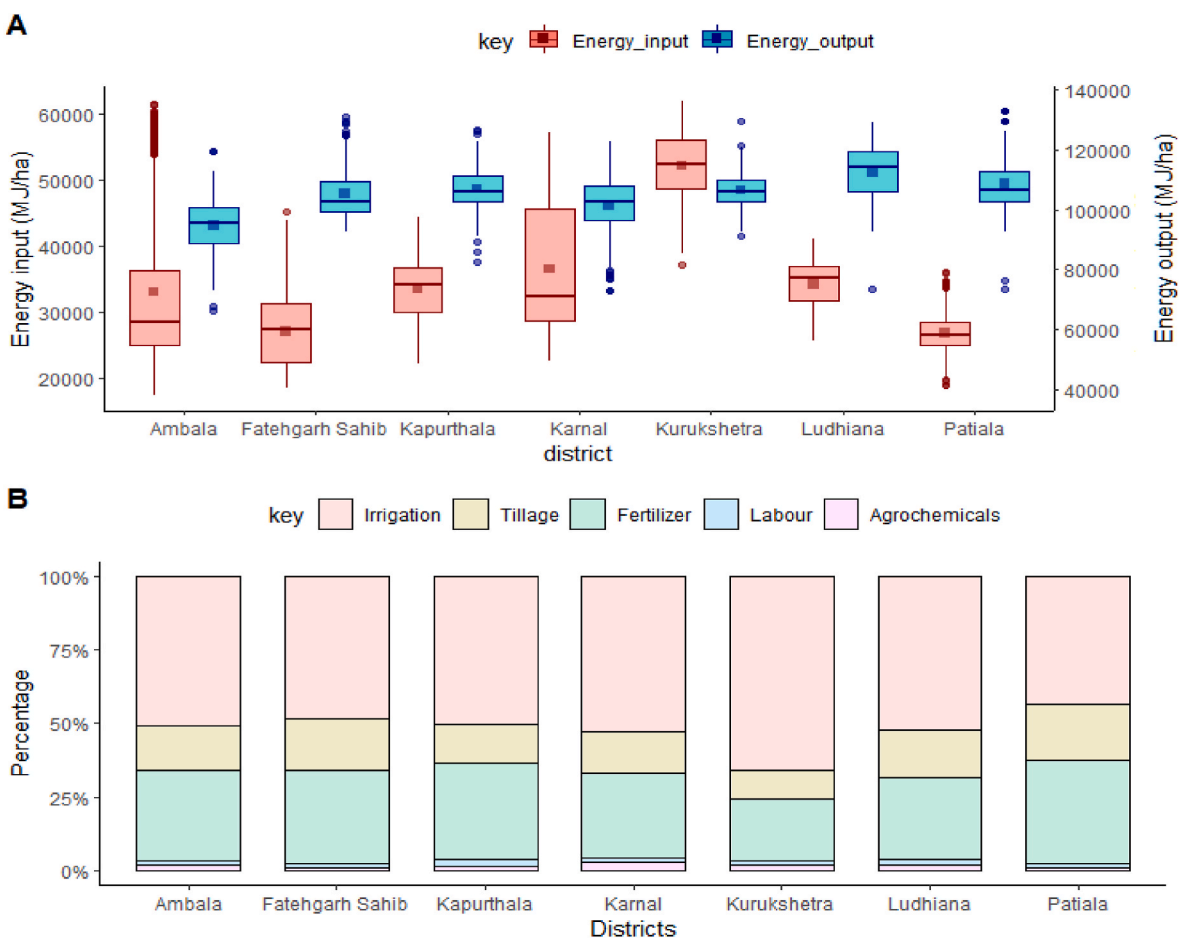

Fig. 3. (A) Variability of energy input (Energy_input; MJ ha^{-1}) from all sources (in primary y-axis) and energy output (Energy_output; MJ ha^{-1}) in rice grain (in secondary y-axis) and (B) share of energy input from different sources across the surveyed districts in the Northwestern Indo-Gangetic Plains of India. The districts Ambala, Karnal and Kurukshetra are located in Haryana state whereas Ludhiana, Fatehgarh Sahib, Kapurthala and Patiala are located Punjab state. Irrigation: Energy input in irrigation; Tillage: Energy input in tillage operations; Fertilizer: Energy input in fertilizer; Labor: Energy input in Labor; Agrochemicals: Energy input in agrochemicals.

depends on the depth of the water table and the pump size. A linear regression was thus fitted between the water table depth and pump size, and between pump size and cumulative hours of irrigation.

3. Results

3.1. Energy use efficiency and main sources of energy use for rice production in Northwest India

The total energy input for rice production across Punjab and Haryana ranged between 18,466–45,119 MJ ha^{-1} and 17,250–61,857 MJ ha^{-1}, respectively, and the energy output from rice grain yield varied between 73,500–132,682 MJ ha^{-1} in Punjab and 66,275-129,361 MJ ha^{-1} in Haryana (Fig. 3A). In Haryana, the lowest mean energy input was observed in Ambala (32,966 MJ ha^{-1}), followed by Karnal (36,4823 MJ ha^{-1}), and the mean energy input in Kurukshetra was 43 and 58% higher than the mean energy input of Karnal and Ambala, respectively (Fig. 3A). In Punjab, the lowest energy input was observed in Patiala and the highest in Ludhiana, the latter having 28% higher average energy input than the former. The EUE varied between 1.24 and 5.93 in Haryana and 1.97–5.89 in Punjab, with a median EUE of 2.43 and 3.61 in Haryana and Punjab, respectively (data not shown).

On average, the largest share of energy input was from irrigation independently of the district, contributing between 43% in Patiala to 66% in Kurukshetra (average = 51.3%) of the total energy input (Fig. 3B). The energy input for irrigation ranged between 4,614–40,000 MJ ha^{-1} in Haryana and 6,708–30,198 MJ ha^{-1} in Punjab (Table 3). The largest variability in energy input for irrigation was observed in Ambala, followed by Karnal and the least variability was observed in the districts of Punjab (Table 3). Next to irrigation, fertilizer manufacturing and application was the second most important source of energy input, accounting for about 21–36% of the total energy input in all districts (Fig. 3B). On average, farms in Kapurthala had the largest energy input from fertilizer (11,001 MJ ha^{-1}), which was 25% higher than those in Fatehgarh Sahib (Table 3). Contrary to irrigation, the variability in energy input from fertilizer use was smallest in Patiala (465 MJ ha^{-1}) and largest in Ambala (1,602 MJ ha^{-1}, Table 3). Tillage operations, and the respective diesel consumption, were the third-largest source of energy input in the surveyed districts (Fig. 3B). Across the districts, rice farms spent 10–19% of the total energy input in tillage operations. Tillage-related energy inputs were highest in Ludhiana (5,595 MJ ha^{-1}) and the lowest in Kapurthala (4,399 MJ ha^{-1}), (Table 3). The average energy input in agrochemicals (herbicide, insecticide, and fungicide) was smallest in Fatehgarh Sahib (269 MJ ha^{-1}) and largest in Kurukshetra (1,048 MJ ha^{-1}, Table 3). Energy input from manual labor was the lowest among all considered sources (Fig. 3B and Table 3).

3.2. Bias corrected group-specific and meta-frontier technical efficiency scores and meta technology ratio

The TE score for all the districts ranged between 0.68 and 0.99, with a mean value of 0.86–0.90. Moreover, farms from Punjab were more homogenous than the farms from Haryana (Fig. 4A). More than 90% of the farms in Ludhiana and Kapurthala had a TE score greater than 0.8, whereas in Patiala and Fatehgarh Sahib, ca. 85% of the farms had TE scores between 0.8 and 1.0, indicating that least efficient farms can reduce energy inputs by 20%, as compared to the most efficient farms in the respective districts, without compromising energy output (Fig. 4A). The TE scores in the districts of Haryana were, on average, smaller than the TE scores in the districts of Punjab, ranging between 0.48 and 0.97 in Ambala and 0.63–0.98 in Karnal and Kurukshetra. A considerable number of farmers (>50%) from Ambala district had TE scores lower than 0.80.

The meta-frontier identifies the efficient farms from all the districts, and the bias-corrected meta-frontier efficiency (ME) score (Fig. 4B) was used for inter-districts comparison of DMU's for energy use efficiency. Alike TE scores, the districts of Punjab had higher ME scores than the districts of Haryana, more specifically, the farms from Patiala and Fatehgarh Sahib districts were most efficient and operating closer to the input-oriented meta-frontier. About 81% and 56% of the farms from Fatehgarh Sahib and Patiala had ME scores greater than 0.75, respectively, whereas all other districts had less than 30% of the farms with a meta-efficiency score as high as 0.75 (Fig. 4B). Only 4–7% of the farms from the Karnal and Kurukshetra had a ME score greater than 0.75. Although farms in Ambala had more heterogeneous TE scores, they had a greater ME score than farms in other districts of Haryana and in the district of Ludhiana. The order of mean ME score was as follows: Fatehgarh Sahib (0.81) > Patiala (0.77) > Ludhiana (0.70) > Kapurthala

Table 3
Energy input by source for rice production across the surveyed districts in the Northwestern Indo-Gangetic Plains of India.

	Ambala (n = 644)	Fatehgarh Sahib (n = 568)	Kapurthala (n = 507)	Karnal (n = 571)	Kurukshetra (n = 619)	Ludhiana (n = 378)	Patiala (n = 546)
Energy use in tillage (MJ ha^{-1})							
min	2808	1270	2409	3068	2067	3116	1872
max	8342	7142	6752	7609	7748	8047	7481
median	5143	5208	4841	5135	4866	5672	5477
mean ± SD	5007 ± 882	4713 ± 838	4399 ± 1094	5152 ± 887	5063 ± 905	5595 ± 853	5083 ± 870
Energy use in mineral fertilizer (MJ ha^{-1})							
min	4880	6125	6474	4880	5880	6274	6274
median	10,490	8505	11,411	10,510	11,411	9510	9410
max	14,627	12,546	14,747	14,758	15,128	13,646	11,501
mean ± SD	10,117 ± 1602	8685 ± 667	11,001 ± 1398	10,845 ± 1440	11,127 ± 1375	9989 ± 1118	9472 ± 465
Energy use in irrigation water (MJ ha^{-1})							
min	4614	6708	11,744	8948	20,132	10,066	7340
max	40,000	30,198	26,843	38,922	40,000	21,608	20,132
median	12,331	13,730	17,783	14,092	34,001	18,848	11,077
mean ± SD	16,771 ± 10,808	13,058 ± 4614	16,837 ± 3307	19,200 ± 8857	34,320 ± 4511	17,799 ± 3011	11,681 ± 2362
Energy use in manual labor (MJ ha^{-1})							
min	186	180	508	265	326	402	208
max	1104	570	902	980	1080	976	413
median	380	323	718	588	752	590	282
mean ± SD	445 ± 156	318 ± 50	715 ± 65	598 ± 116	766 ± 98	636 ± 108	288 ± 31
Energy use in agrochemicals (MJ ha^{-1})							
min	25	28	6	102	46	82	50
max	1777	1676	1779	2841	2296	1974	1647
median	688	217	328	1023	1050	408	250
mean ± SD	625 ± 404	269 ± 253	532 ± 471	1028 ± 624	1048 ± 437	714 ± 560	282 ± 132

Min: Minimum value; max: Maximum value; SD: standard deviation.

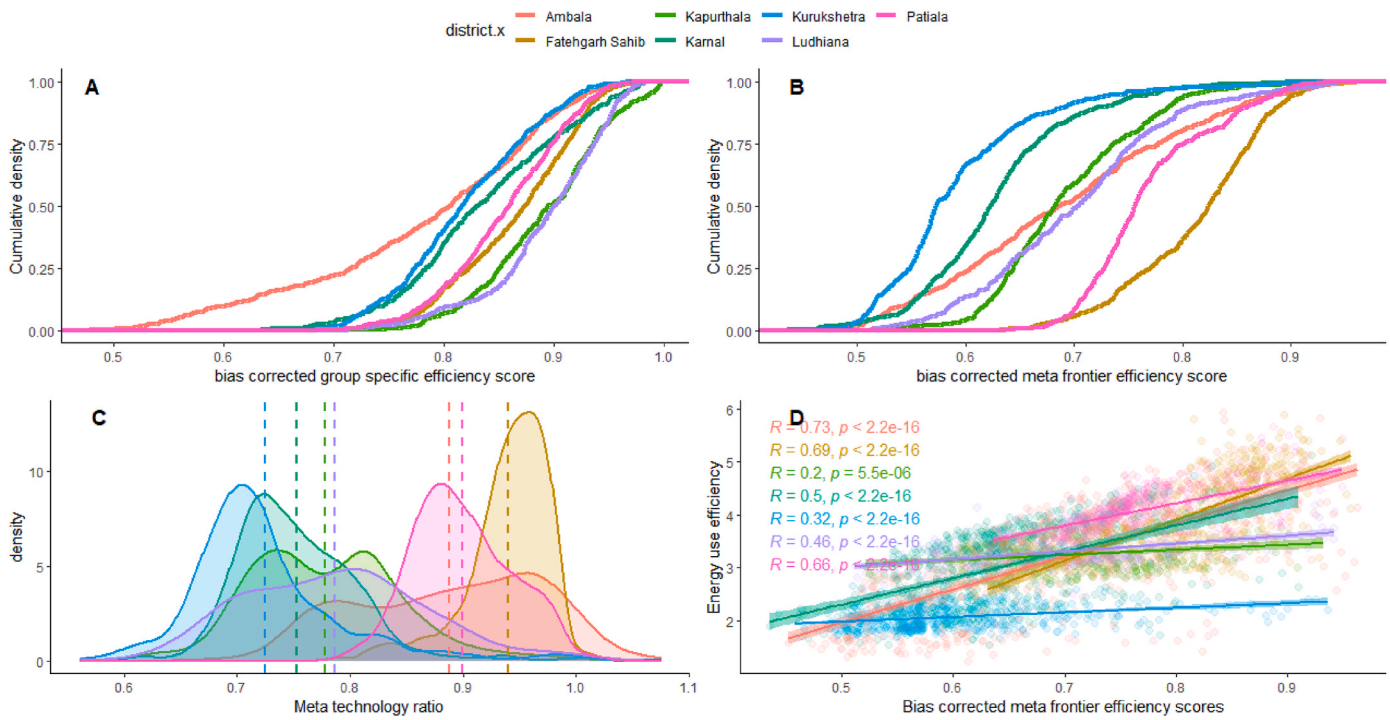

Fig. 4. Cumulative density distribution of the bias-corrected district-specific efficiency score (A) and meta-frontier efficiency score (B); density plot of the meta-technology ratio (C) and, variation between meta-frontier efficiency score and energy use efficiency (D) for rice production in the Northwestern Indo-Gangetic Plains of India.

(0.69) > Ambala (0.69) > Karnal (0.63) > Kurukshetra (0.59).

A higher value of the meta-technology ratio (MTR), i.e., the ratio between group-specific TE score and ME score, indicates that a given district has access to adequate resources, improved technologies, and/or more favorable biophysical conditions than other districts. Farms in Fatehgarh Sahib had the greatest mean MTR (~0.94) followed by farms

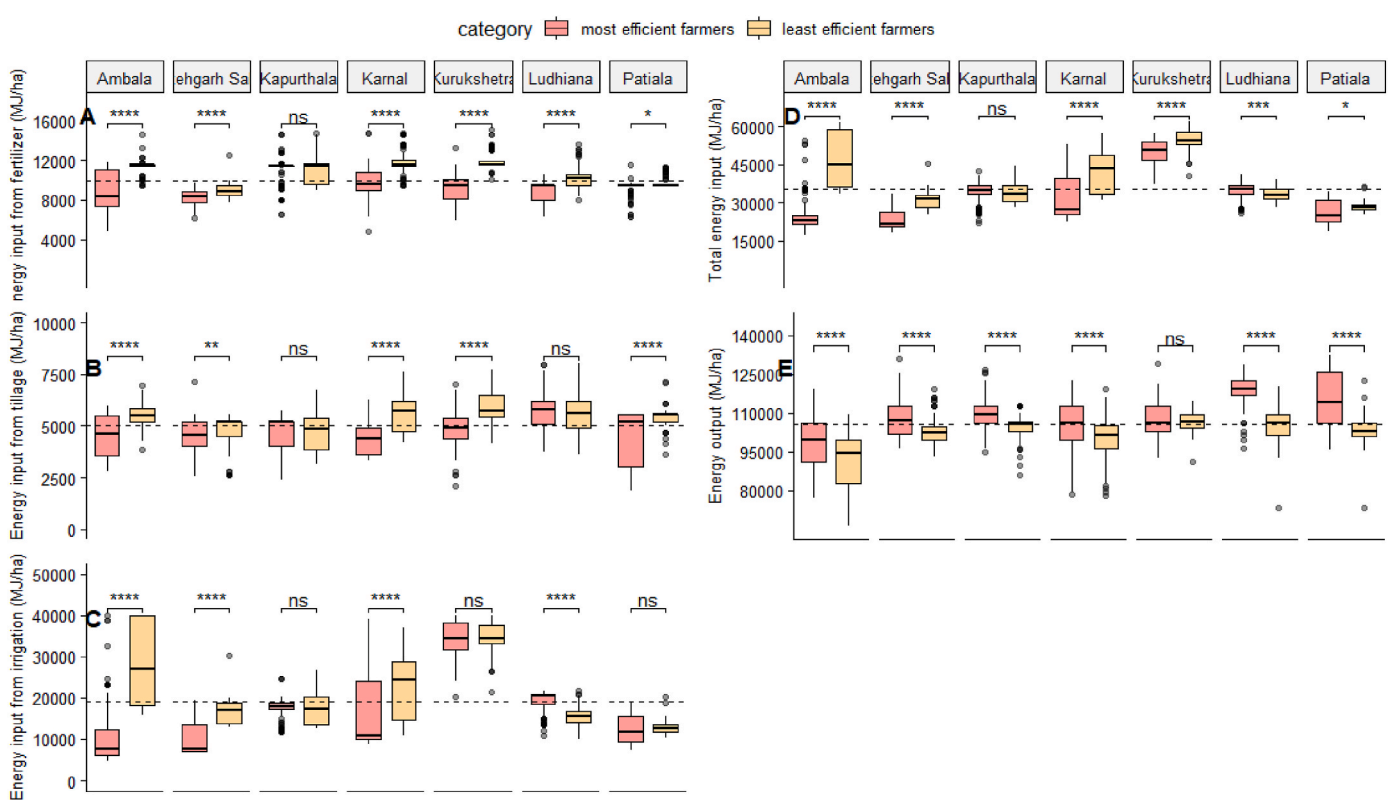

Fig. 5. District-wise differences in energy input used for rice production from fertilizers (A), tillage operation (B), irrigation (C), and total energy input (D) and energy output (E) between top 20% energy use efficient farms and the bottom 20% least energy use efficient farms in the Northwestern Indo-Gangetic Plains of India.

in Patiala (0.90) and farms in Ambala (0.88) (Fig. 4C). Farms in all other districts (i.e., Kapurthala, Karnal, Kurukshetra, and Ludhiana) had nearly similar mean MTR (0.71–0.76) and distribution of MTR (Fig. 4C). The latter indicates that if farms in the districts with low mean MTR could adopt the management practices observed in farms across Patiala and Fatehgarh Sahib (assuming no major biophysical constraints), then it would be possible to further increase the EUE of rice production in the Northwestern IGP of India. All surveyed districts exhibited a significant positive correlation between ME score and EUE, although the strength of the correlation varied between the districts (Fig. 4D). The significant linear relationship indicates that increases in efficient crop management can lead to improvements in EUE in all districts.

3.3. Categorization of farms as most and least efficient based on efficiency scores

There were marked differences in the energy input used in the different operations, the cumulative energy input, energy output, and EUE between the most and least energy use efficient farms in all districts (Fig. 5). Considering the energy input for fertilizers, all districts except Kapurthala had significantly different energy use between the most and least energy use efficient farms (Fig. 5A). The largest difference in the energy input for fertilizers between most and least efficient energy use farms was observed in Kurukshetra and Ambala, where the most energy use efficient farms used ca. 30% less energy in fertilizers than the least energy use efficient farms. Similarly, the most energy use efficient farms in Karnal, Ludhiana, and Fatehgarh Sahib used 21, 17, and 7% less energy input in fertilizers than least energy use efficient farms, respectively. Energy input from tillage operations was also significantly different between the most and the least energy use efficient farms, yet the differences in energy input for tillage operations between both groups were small (Fig. 5B). The latter was true for all districts except for Kapurthala and Ludhiana where the most and the least energy use efficient farms had a similar energy input for tillage operations. The mean energy input for tillage operations of the most energy use efficient farms from all the districts of Haryana and Patiala district in Punjab was 21–26% lower than that of the least energy use efficient farms in the respective district (Fig. 5B).

The energy input for irrigation was similar between the most and the least energy use efficient farms in the districts of Patiala, Kapurthala, and Kurukshetra, whereas significant differences in energy input for irrigation were observed between both groups in all other districts (Fig. 5C). The mean energy input for irrigation by the most and least energy use efficient farms in the district of Kurukshetra (ca. 34,500 MJ ha^{-1}) was greater than the mean energy input for irrigation of the pooled sample (ca. 18,802 MJ ha^{-1}), while in the district of Kapurthala the energy input for irrigation (ca. 17,800 MJ ha^{-1}) was closer to mean energy input for irrigation observed for the pooled sample (Fig. 5C). A minimum of 42% less energy was used for irrigation by the most energy use efficient farms in Ambala, Fatehgarh Sahib, and Karnal districts. In Ludhiana, the most energy use efficient farms had a greater energy input use for irrigation than least energy use efficient farms (19,117 vs. 15,925 MJ ha^{-1}; Fig. 5C). The total energy input was significantly different between the most and the least energy use efficient farms in all the districts except Kapurthala (Fig. 5D). Overall, the most energy use efficient farms in Karnal, Fatehgarh and Ambala used 25% less energy input than the least energy use efficient farms in the same districts, whereas the difference between both groups was only 9% in Kurukshetra. In Ludhiana, the most energy use efficient farms had a slightly greater mean energy input than the least energy use efficient farms (34,656 vs. 33,428 MJ ha^{-1}).

Energy output from rice production was significantly different between the most and the least energy use efficient farms in all the districts, except Kurukshetra (Fig. 5E). In all districts, the most energy use efficient farms had higher energy output in the range of 5–12% than the least energy use efficient farms. Overall, the most energy use efficient farms from Karnal, Fatehgarh Sahib and Ambala used 25% less energy input than least energy use efficient farms in the respective districts, whereas that difference was 9% lower in Kurukshetra (Fig. 5D). In Ludhiana, the most energy use efficient farms had slightly greater energy input than the least energy use efficient farms. On average, the most energy use efficient farms had 42% or higher EUE than the least energy use efficient farms in the districts of Ambala, Fatehgarh Sahib, and Karnal, whereas in other districts EUE in the most energy use efficient farms were 5–19% higher than in the least energy use efficient farms.

3.4. Key determinants of energy use efficiency

Agronomic practices had a prominent effect on the ME scores whereas the effect of socio-economic characteristics was rather small (Table 4). It was observed that ME scores increased with increases in landholdings and with decreases in family size (Table 4). For some of the variables, the response was consistent across the meta-frontier and most of the district-specific frontiers, like the intensiveness of herbicide and insecticide use: more frequent application of insecticides and herbicides significantly affected the energy use efficiency in a negative way across all districts (Table 4). Advancing sowing dates beyond the 132nd Julian day had a consistently positive impact on the ME scores in the meta-frontier and in the district-specific frontier for Ambala and Patiala, but the effect size was very small (Table 4). The depth of the water table had a significant negative effect on the ME scores across all districts. Overall, in the meta-frontier, as well as in the Karnal, Ambala, Kapurthala, and Fatehgarh Sahib district-specific frontiers, when the water table depth was less than 90 feet, the average ME score increased by up to 0.15 than where the water table was deeper than 90 feet (Table 4). In the districts of Kurukshetra, Patiala, and Ludhiana, the average ME score was lower when the water table was less than 90 feet deep. In the meta-frontier model and in Ambala, Fatehgarh Sahib, and Patiala district-specific frontiers, crop duration had a significant positive effect on ME score in the range of 0.001–0.003 (Table 4). Finally, the effects of the 1st and 2nd top-dress of urea on the ME score varied across the districts and in the meta-frontier model both in direction and amount.

4. Discussion

4.1. Energy input for rice production in the Northwestern IGP of India

The intensive rice production systems in the Northwestern IGP of India are characterized by high yields but also by significant energy input. This is primarily due to the nature of rice cultivation, which requires large amounts of water and fertilizers. Irrigation and fertilizer application were found to be the main sources of energy input in this region (Fig. 3). However, inefficiencies in the management of these operations are prevalent, as farmers tend to over-irrigate their fields due to the availability of nearly free electricity and the impact of subsidized fertilizer policies. This leads to the application of irrigation and fertilizer at rates higher than recommended, leading to higher energy investments in rice production than necessary. This is consistent with previous research that has found low irrigation water productivity and N-use efficiency in the Northwestern IGP of India [34]. Our findings are in line with the work of Basavalingaiah et al. [6] and Sekar and Pal [35], who also reported irrigation and fertilizers as the dominant sources of energy input for rice production.

The present study found that electricity for irrigation accounted for a substantial share of the total energy input in rice production in the Northwestern IGP of India (Fig. 3). This is in line with previous studies, such as Singh et al. [5], which also identified irrigation as the main source of energy consumption. It was observed that there was significant variability in energy use for irrigation across different farms (Table 3), which can be attributed to factors such as pump size, water table depth, irrigation time, and frequency of irrigation. The accurate information on soil hydrological properties or texture can be use full for improving the

Table 4
Determinants of the energy use efficiency for rice farms in the Northwestern Indo-Gangetic Plains of India. Data refer to the pooled sample and district-specific sample from the meta-frontier technical efficiency score, right truncated around the maximum values, the point of truncation is presented in the brackets. The variable "water table depth less than 90 feet" is categorical with two alternatives, less than 90 feet or more than 90 feet. The "soil texture" variable is also categorical with the alternatives light and medium textured soil.

Variables	Pooled data (0.9623)	Ambala (0.9623)	Karnal (0.9089)	Kurukshetra (0.9359)	Kapurthala (0.9315)	Ludhiana (0.9416)	Patiala (0.9484)	Fatehgarh Sahib (0.9561)
Intercept	0.272***	0.210**	0.662***	−0.248	1.443	0.696***	0.219***	0.757***
Delay in sowing beyond 132nd Julian days	0.003***	0.003***	−0.001	−0.003	0.008	−0.001	0.004***	0
Water table depth less than 90 feet	0.039***	0.147***	0.034***	−0.001*	0.000#	−0.113***	−0.038***	0.077***
Age of household head (yr)	0.001***	0.001*	0	−0.001	0	0	0.000#	−0.001**
Land holding size (ha)	0	0	0	−0.001	0	0.001*	0.001***	0.001*
Family size (number)	−0.002*	0	0.001	0	0	−0.001	−0.006***	0.001
Crop duration (days)	0.003***	0.002***	0	0.005	−0.006	0	0.003***	0.001#
1st urea top dress (days after transplant)	0.010***	0.001	0.001	0.010***	−0.006*	−0.004	−0.002	0.003
2nd urea top dress (days after transplant)	−0.006***	0.003*	0.001	0.004**	0.006**	0.007*	0.004***	−0.003
Medium textured soil	0.020***	0.018*	−0.003	0.004	0.006	−0.004	0.002	0.001
Fungicide used (kg ai kg^{-1} of formulation)	0.009**	−0.004	0.019***	0.031***	−0.022***	−0.01	−0.011*	−0.002
Herbicide used (kg ai kg^{-1} of formulation)	−0.005	−0.001	−0.018#	−0.016**	−0.040***	−0.042*	−0.013*	0.008
Insecticide used (kg ai kg^{-1} of formulation)	−0.018***	−0.033***	−0.011***	−0.014**	−0.005	−0.016***	−0.008*	−0.003
sigma	0.100***	0.097***	0.068***	0.066***	0.062***	0.075***	0.051***	0.054***

Significant codes: *** indicates significance at $P < 0.001$, ** indicates significance at $P < 0.01$, * indicates significance at $P < 0.05$ and # indicates significance at $P < 0.1$.

estimates of efficiency of energy use, as these parameters governs the frequency of irrigation. The decline of the groundwater table in the IGP has led farmers to invest in high-capacity pumps in recent years [36,37]. Our data showed a strong correlation between the median water table depth and pump size (R = 0.73; Fig. 6a), indicating that pump size increased in areas with a deeper groundwater table. However, no evidence was found to suggest that farmers installed higher power pumps in areas with shallow water tables to reduce irrigation time. On the contrary, a negative relationship was observed between the cumulative duration of irrigation and pump size (R = −0.23; Fig. 6B), suggesting that farmers irrigated slightly less in areas with deeper water tables and higher pump power requirements. These findings suggest that the declining groundwater table in the region may be contributing to the reduced energy use efficiency among some farmers. The installation of high-capacity pumps to overcome declining water levels has likely increased energy consumption in some instances, despite efforts to conserve water and reduce irrigation time. Such area may be avoided for future rice production in lieu of sustainable use of ground water for multiple purposes and energy conservation.

The findings of our study align with previous on-station trials that have identified irrigation and fertilizers as significant sources of energy in conventional rice farming [11]. However, our results showed that the energy input in irrigation in farmers' fields was higher than in research trials, indicating a need for better management practices (Table 3). This highlights the importance of comparing farmers' practices to the most energy efficient practices in the study region and identifying opportunities for improvement. Future research could explore the potential of promoting improved agronomic practices that could further enhance

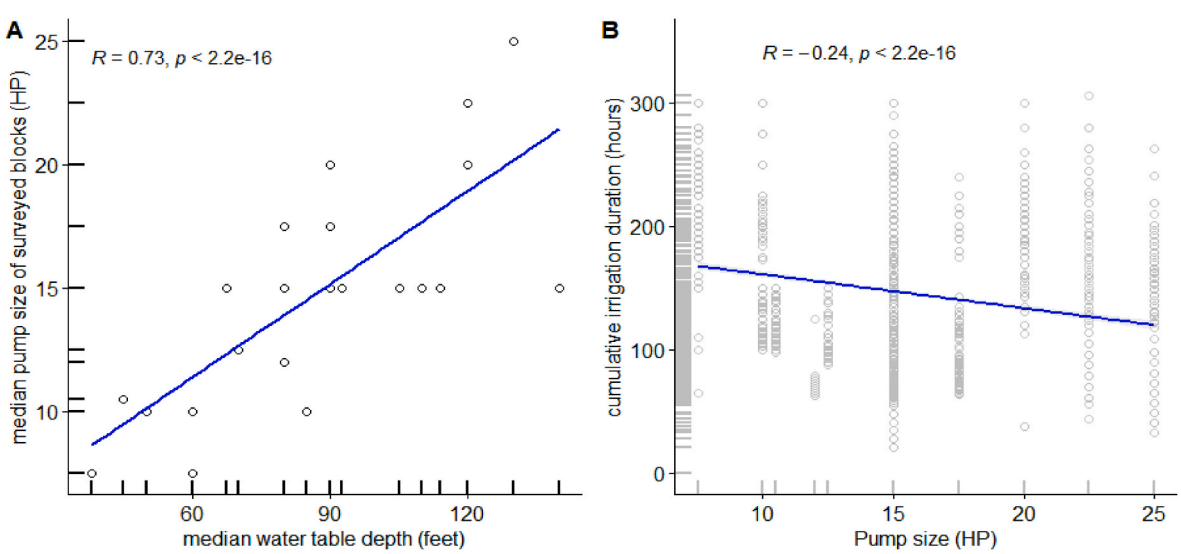

Fig. 6. Relationship between median water table depth and median pump size across the surveyed districts (A) and relationship between pump size and cumulative irrigation duration (B) for all sampled fields. Blue lines show linear regressions fitted to the data. P indicates the significance level of regression coefficients. Pump size expressed in power unit: 1 HP = 746 W and water table depth in feet, 1 feet = 0.3048 m.

energy use efficiency in the rice farming sector. Such an effort could lead to significant energy savings and contribute to sustainable rice production in the Northwestern IGP of India. Such practices may not be currently used at on-farm level making it difficult to explore their benefits at farm level.

4.2. Improving energy use efficiency through reduced tillage, irrigation, and fertilizer use

Effective energy use is crucial to mitigate environmental problems and avoid the high economic costs associated with inefficient energy use, particularly for non-renewable resources. Our analysis, based on the differences in energy use between the most and least efficient farms (Fig. 5D and E), suggests that there is a potential to reduce energy inputs, especially those related to irrigation and fertilizer use (Fig. 5A and C), while maintaining energy output. Other studies, such as those by Basavalingaiah et al. [6] and Mohammadi et al. [38], also found that reducing fertilizer and irrigation inputs is essential for improving energy use efficiency in rice and soybean farms, respectively. In our study, we observed that the most energy efficient farms applied N fertilizers at recommended levels (i.e., 148 kg N ha^{-1}), while least efficient farms applied 22 kg more N per hectare and 10 kg more P_2O_5 per hectare than recommended, leading to higher energy inputs without proportional increases in energy output (data not presented). This result is consistent with previous studies by Bhatt et al. [34] and Sekar and Pal [35] which reported high fertilizer use in rice production, alike high-input cropping systems elsewhere [47]. Additionally, tillage was another significant source of energy use, with increased tillage operations and frequent use of wet harrow for puddling decreasing energy use efficiency in the least energy efficient farms. The impact of puddling intensity on crop productivity and energy output has been a subject of debate in the past [39,40].

Although many resource conservation practices have been suggested to improve energy use efficiency in the Northwestern IGP of India, those are not widely adopted by farmers. For instance, conservation agriculture based direct-seeded rice production technology [41], tensiometer based irrigation [42], site-specific nutrient management using leaf color charts, chlorophyll meters, or other decision support tools [11,33,43,44] are the proven technologies having energy saving potential under research trials. Field adoption of resource conservation practices provides a basis to improve energy use efficiency at the farm level, but needs to be embedded within policies that provide incentives for farmers to save resources. Alternatively, some easy to scale technologies which are already in use in farmers' field, like precision irrigation based on tensiometer, fertilizer recommendation based on site-specific nutrient management principles, and adoption of minimum tillage are the entry point to improve energy use efficiency.

4.3. Determinants of energy use efficiency and opportunities for improvement

Our analysis revealed several key determinants of energy use efficiency in the Northwestern IGP of India, including pest management, water table depth, crop duration, and fertilizer management. The frequency and amount of insecticide and herbicide applications were positively correlated with lower energy use efficiency (Table 4). In intensive production systems where high output levels are desired, efficient pest, disease, and weed management is crucial to avoid crop losses. However, frequent application of agrochemicals results in lower energy output and energy use efficiency [45,46]. Additionally, the depth of the water table was found to be an important factor, with farms having a water table depth less than 90 feet exhibiting higher energy use efficiency compared to those with deeper water tables. In the latter cases, greater energy inputs are required to extract irrigation water. Crop duration was also a determinant of energy use efficiency, with long-maturity varieties resulting in greater ME scores and EUE due to similar energy inputs, except for irrigation (data not presented). Furthermore, the timing of fertilizer management, specifically the 1st and 2nd split of urea, was found to have a significant impact on ME scores, suggesting that fine-tuning N management could lead to improved energy use efficiency. Overall, these findings highlight the importance of addressing these determinants in efforts to improve energy use efficiency in rice cultivation in the Northwestern IGP of India.

Contrary to on-station research on energy saving potential and meta-analysis [48], estimation of energy savings from the farm survey data were mostly done by peer-to-peer comparison using DEA. For DEA analysis, DMUs must represent a diversity of input-output combinations to effectively estimate technical efficiency scores. Yet, field surveys are prone to sampling errors. DEA is particularly sensitive to outliers due to its deterministic approach to frontier analysis, meaning that the presence of outliers can provide unrealistic benchmarks for all DMUs and thus unrealistic estimates of technical efficiency. Such limitation was overcome by adopting a bootstrapped DEA approach, supplemented with truncated regression. The two-stage approach followed here provides an indication of the energy savings possible to obtain for a given level of energy output (Fig. 5) and identifies key determinants of energy use efficiency (Table 4). The approach can be further strengthened with the availability of more precise soil and weather data. Soil and weather data can help to better disentangle the effect of biophysical factors from that of crop management practices on energy use efficiency as these allow to group farms with homogenous biophysical conditions prior to the analysis. Further, the methodology can be applied to other performance indicators to assess whether farms with low efficiency in energy use also perform worse in terms of profit or greenhouse emissions.

5. Conclusion

Competition for energy between different economic activities demands efficient energy use in the agricultural sector, particularly in intensive cropping systems. Electricity energy for irrigation and energy input through fertilizers were two major activities accounting for more than 75% of the total energy input used for rice production in the Northwestern Indo-Gangetic Plains of India. We observed a large disparity among farms in terms of energy use efficiency, and in all the districts surveyed it is possible to reduce the energy input in different operations yet without reducing energy output. It is possible to improve energy use efficiency by at least 42% in the districts of Ambala, Fatehgarh Sahib, and Karnal, whereas in other districts energy use efficiency can be increased by 5-19%. The timing and amount of irrigation, as well as timing and amount of fertilizers deserve particular attention due to their large share on the total energy input and their over-application in the least energy use efficient farms. Least efficient farms opted for higher number of tillage operations like wet harrowing and intensive puddling, which must be reduced to increase energy-use efficiency. Further, fine tuning sowing dates, along with timely pest and weed management can improve energy use efficiency in the future. Precision fertilizer application along with optimizing the irrigation number and tillage practices are the key to improve energy-use efficiency of rice farms in the Northwest India. The methodology and evidence provided in this study can help formulate district-specific action plans for sustainable intensification of rice production in the Northwestern IGP of India and can be extended to other production systems and performance indicators. The latter is paramount given the environmental and economic concerns associated with inefficient resource use in the Green Revolution corridor of India. Our study is thus helpful to guide policymakers and researchers in identifying pathways towards sustainable energy use for rice production in the future.

Author contribution

HSN, SA, TBS, CMP, JVS, TJK, MLJ: Conceptualization, Investigation, TBS, TJK: Funding acquisition, SA, HSN, JVS: Data Formal analysis,

Writing draft, Review of the draft, SKK, DRS, DB, LKS, MK, KMC, TBS, TJK: Field investigation, Review, SK, YK, HSJ, HSS: Field investigation, writing draft, AJM, SS, VK: Reading and revision of manuscript.

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.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.energy.2023.126986.

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