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# Ensuring sustainable crop production when yield gaps are small: A data-driven integrated assessment for wheat farms in Northwest India

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## ABSTRACT

Northwest India achieved remarkable wheat productivity gains during the past decades. However, this has been accompanied by increasing input levels and intensive production practices, raising questions about the economic and environmental sustainability of current cropping systems. A multicriteria integrated assessment is required for wheat farms in the region to understand the scope for cleaner wheat production in the future. Production practices from irrigated wheat fields (n = 3928) were evaluated for multiple sustainability indicators, namely yield gap, nitrogen (N)-use efficiency, profitability, and greenhouse gas emissions. Stochastic frontier analysis was combined with simulated potential yield (Yp) data to identify the causes of wheat yield gaps in the region. N-use efficiency was estimated by calculating the partial factor productivity of N, profitability was computed based on reported input-output amounts and prices, and greenhouse gas emissions were quantified using the Mitigation Options Tool (MOT). These indicators were subjected to a multicriteria assessment using the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) under different scenarios (i.e., different weights for different indicators). For each scenario, farmers' fields were classified as most efficient, efficient, less efficient, and least efficient, and random forest was used to identify the most important management practices governing the field classification. Wheat yield gaps were small (25–30 % of Yp or 2.4 t $ha^{-1}$) and mostly attributed to the technology yield gap (ca. 20 % of Yp or 1.5 t $ha^{-1}$). Ranking and grouping the farmers' fields in the scenario with equal weights for all indicators revealed that at least 25 % of the fields had very high greenhouse gas emissions (>1500 kg $CO_2$-eq $ha^{-1}$) at a productivity level of < 4.5 t $ha^{-1}$, and that it is possible to produce wheat sustainably without compromising yields in Northwest India, as indicated by the performance of the most efficient fields. Tillage intensity and N application rates can be adjusted for least efficient fields (<10 % least efficient fields adopting zero tillage vs >80 % most efficient fields adopting zero tillage) to achieve an overall objective of higher yield, lower greenhouse gas emissions, more profit and higher N-use efficiency, whereas residue retention and tillage intensity would need to be prioritized for minimizing greenhouse gas emissions. For the most efficient fields the decrease in greenhouse gas emissions was always associated with a decline in yield level. The most important management practices governing the field classification included the crop establishment method used for the previous rice crop, the number of tillage operations, residue retention, and the N fertilizer rate for wheat. The study provides a data-driven approach to screen trade-offs between performance indicators and to identify the management practices that can deliver sustainable and cleaner crop production in the future.

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## 1. Introduction

Rice-wheat cropping systems prevail across the Indo-Gangetic Plains (IGP) in South Asia (Bhatt et al., 2021). Wheat is the second most important cereal crop in India after rice, being cultivated during the winter season on 31.4 Mha with a total production of 107.6 Mt in recent years (ICAR data book, 2021). Farmers in the Northwestern IGP use intensive crop production practices and achieve relatively high yields (Nayak et al., 2022). Yet, it remains important to understand to what extent wheat production can be further increased as wheat demand is expected to rise by about 60 % in the IGP by 2050 (Rosegrant et al., 2009). At the same time, there are concerns of sustainable resource use in the region (Nayak et al., 2022; Jat et al., 2020, 2020a; Jat et al., 2020, 2020aa), which require a better understanding of the environmental losses and economic profitability associated with on-farm wheat production. Rice-wheat cropping systems face multiple challenges due to the different agronomic needs of rice and wheat and the intensive use of resources. This has led to declining soil fertility and a notable slowdown in yield progress. Consequently, production becomes increasingly less profitable as resources become scarcer (Chauhan et al., 2012). Improving the sustainability of crop production in the region requires understanding synergies and trade-offs between different production, socio-economic, and environmental dimensions, as an entry point to identify farming practices that balance multiple benefits simultaneously. Yield gap closure and profitability are among the main sustainability priorities for farmers, whereas greenhouse gas emissions and nutrient use efficiency are increasingly important for society at large.

Narrowing yield gaps on existing cropland is crucial for future food security. However, sustainable and cleaner crop production requires more than yield gap closure (Nayak et al., 2024). In this context, we refer to sustainable and cleaner production as the ability of farms to improve productivity and profitability per unit of resource use and environmental footprint (Nayak et al., 2024). The yield gap, defined as the difference between the potential yield and the actual farm yield, is vital for understanding how efficiently land is used. Establishing the relationship between yield gap closure and other sustainability indicators helps identify the synergies and trade-offs for future crop production intensification. Farmers prioritize profitability, making it essential to consider economic viability alongside productivity (Silva et al., 2017; Van Dijk et al., 2017). However, crop production contributes to greenhouse gas (GHG) emissions, emphasizing the need for multifaceted assessments to guide sustainable farming practices (Sapkota et al., 2019). Comprehensive assessments have been conducted on how field-level technologies (e.g., minimum tillage, precision fertilizer management, tensiometer-based irrigation) affect wheat productivity, profitability, and environmental sustainability across the IGP (Harrington, 1992; Krishna and Veettil 2014; Aryal et al., 2015; Jat et al., 2019, 2019a; Jat et al., 2019, 2019aa). Yet, no comprehensive assessment has been conducted to identify which management practices already used by farmers can best contribute to sustainable wheat production according to multiple performance indicators. In low-input cropping systems, increased input use often increases crop productivity and creates synergies among sustainability indicators. However, in high-input cropping systems, such as those in Northwest India, additional inputs often do not increase yields but instead increase environmental externalities, intensifying trade-offs between different sustainability dimensions (Nayak et al., 2022; Tseng et al., 2021; Tahmasebi et al., 2018).

Previous studies examined yield gaps and associated indicators in various agricultural contexts but often lacked quantitative multicriteria assessments (e.g., Silva et al., 2021, 2017). Therefore, our study aims to fill this gap by evaluating wheat production practices across multiple sustainability indicators using a multicriteria assessment framework. Using data from 3928 farmer fields collected during the 2020–2021 growing season, we conducted a multicriteria assessment to benchmark wheat production in Northwest India. The objectives of this study were to: (1) identify the causes of wheat yield gaps, (2) benchmark on-farm wheat production according to multiple sustainability indicators, and (3) assess synergies and trade-offs between the different indicators and identify important management practices contributing to sustainable and cleaner wheat production under different scenarios. Similar to rice (Nayak et al., 2022), we hypothesize that wheat yield gaps in Northwest India are about 20 % of Yp. Moreover, we expect some farms to achieve high wheat yield with low profitability, N-use efficiency, and high GHG emissions, while other farms are able to reconcile high productivity with sustainable wheat production from an economic and environmental perspective.

## 2. Material and methods

### 2.1. Survey data collection

Crop management practices from wheat farms in Northwest India were collected using a structured questionnaire administered by trained enumerators at the end of the cropping season and supplemented with crop-cut yield estimation from the largest plot. Data collection was performed using an Android-based Open Data Kit (ODK) platform (Ajay et al., 2022). Details of the survey questions and descriptive statistics of the key variables can be obtained from Nayak et al. (2022a). One-dimensional outliers were identified using boxplots and histograms, while two-dimensional outliers were identified using Mahalanobis distance (see Nayak et al., 2022a, for further details).

The diesel used for tillage operations was cross-verified against the tillage cost and intensity of tillage reported by the farmers. A minimum threshold for labor use, based on expert knowledge, was applied to correct cases where family labor use was unreported or underreported at unrealistically low values. Weather and soil data for each field were retrieved using the respective GPS coordinates from secondary sources. Cumulative solar radiation and average minimum and maximum temperatures during the growing season were obtained from the ERA5 hourly reanalyzed database (Sabater, 2019). Cumulative rainfall during the growing season was derived from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS; Funk et al., 2015). Soil texture data were obtained from Hengl et al. (2017). A total of 3928 farm-fields were used for yield gap and multicriteria analysis. We excluded from the multicriteria analysis fields with wheat yields below 3 t $ha^{-1}$ and fields sown before 15th October, as the method can be sensitive to outliers. Fields were spread across three districts in Haryana (Ambala, Karnal, and Kurukshetra) and four districts in Punjab (Ludhiana, Patiala, Fatehgarh-Sahib, and Kapurthala) in India. Further details about village, block, and farmer selection are provided in Nayak et al. (2022a); (2022).

Self-reported wheat production and field area data were verified with crop cuts conducted in about 25 % of the fields surveyed, where a $2 \times 2$ $m^2$ quadrat was used to sample from a representative area in the center of the field. The harvested grain was threshed and weighed to measure wheat yield. The moisture content was measured using a handheld grain moisture meter and used to adjust the fresh-weight grain yield to a standard moisture content of 14 %. A linear regression model was fitted between the crop-cut yield and the self-reported yield. Given the good agreement between self-reported and crop-cut yields ($R^2$ of 0.80; Nayak et al., 2022a), the fitted regression model was used to adjust the self-reported yield in the fields where crop cuts were not conducted.

### 2.2. Yield gap analysis

Wheat yield gaps were estimated as the difference between the simulated potential yields and the actual farm yields (van Ittersum et al., 2013). A yield gap decomposition was further conducted to quantify the efficiency, resource, and technology yield gaps (Silva et al., 2017) and identify the key limiting factors to wheat production in Northwest India, as explained below.

#### 2.2.1. Efficiency yield gap

The efficiency yield gap refers to the difference between technical efficient yields ($Y_{TEx}$, i.e., the maximum yield that can be obtained for a given input level in a well-defined biophysical environment) and actual farm yields (Ya; Silva et al., 2017). Differences in yields between two fields with the same input levels can be explained by sub-optimal crop management regarding the timing, placement, and form of the inputs applied, which are the key drivers of the efficiency yield gap.

A Cobb-Douglas functional form considering first-order inputs only was assumed for the relationship between wheat yield and a vector of biophysical factors and crop management practices as follows:

$$\ln y_i = \beta_0 + \sum_{k=1}^{K} \beta_k \ln x_{ki} + v_i - u_i \quad (1)$$

$$\text{Eff. } Yg_i = 1 - \exp(-u_i) \quad (2)$$

$$Y_{TExi} = Ya_i / \exp(-u_i) \quad (3)$$

Technical efficient yields ($Y_{TEx}$), and the associated efficiency yield gaps, were estimated for each field using stochastic frontier analysis (Kumbhakar and Lovell, 2000) in combination with concepts of production ecology (van Ittersum and Rabbinge, 1997) (Eqs. 2 and 3). Stochastic frontier analysis is an econometric approach to assess input-output relationships, which considers two random errors, namely random noise ($v$) and technical inefficiency ($u$). The random error $v_i$ is assumed to be independently and identically distributed (i.i.d.) following a N (0, $\sigma_v^2$) distribution, while the random error $u_i$ is assumed to be i.i.d. following a $N^+(0, \sigma_u^2)$ distribution.

The vector of input variables, $x$, was designed according to concepts of production ecology (van Ittersum and Rabbinge, 1997) to account for growth-defining factors (average maximum and minimum temperatures during the growing season, sowing date, seed rate, and growing season duration), growth-limiting factors (growing season precipitation, number of irrigations, N and P applied, residue retention, and soil texture), and growth-reducing factors (tillage intensity for the previous rice crop, tillage intensity for wheat, weed severity, lodging category, and herbicide, fungicide, and insecticide applied). The Variance Inflation Factor (VIF), as implemented in the *vif()* function of the 'car' package in R (Fox and Weisberg, 2019), was used to assess multi-collinearity between input variables. Variables with a VIF value above 5 were assumed to be collinear, and hence not included in the analysis. The latter included cumulative solar radiation during the growing season, mean temperature during the growing season, insect and disease severity, and crop establishment method. Continuous variables were mean-scaled and log-transformed, such that model parameters can be interpreted as elasticities, prior to fitting the models with the *sfa()* function of the 'frontier' R package (Coelli and Henningsen, 2020). Inefficiency effects included the dates of the first and second urea topdressing and the date of the first herbicide application.

#### 2.2.2. Resource yield gap

The resource yield gap from a production perspective refers to the difference between the highest farmers' yields ($Y_{HF}$) and the $Y_{TEx}$ estimated using stochastic frontier analysis (Section 2.2.1) and can be attributed to sub-optimal amounts of inputs applied (Silva et al., 2017). $Y_{HF}$ was estimated as the mean actual yield above the 90th quantile of actual yields for a given soil type. It was not possible to estimate $Y_{HF}$, and the resource yield gap, by climate zone and variety type, as all fields were in the same climate zone and reported the same variety type.

#### 2.2.3. Technology yield gap

The technology yield gap refers to the difference between Yp, simulated with crop growth models, and $Y_{HF}$, hence reflecting resource yield gaps of individual inputs and/or technologies used by farmers not being able to reach Yp (see Silva et al., 2017, for further explanation). The technology yield gap was estimated for each field as the difference between the Yp retrieved from the Global Yield Gap Atlas and $Y_{HF}$ estimated from the farmer field database (Section 2.2.2). The Global Yield Gap Atlas provides data on the potential yield for irrigated wheat in India simulated with the APSIM crop model (Holzworth et al., 2014) for the winter season over the years 1991–2014. The reader is referred to www.yieldgap.org/India for further details about the crop model parametrization, weather data used, and cropping systems considered in the simulations.

The simulated Yp should ideally match the year of the actual yield data, but this was not possible due to the lack of up-to-date simulated yield data in the Global Yield Gap Atlas. Therefore, the average Yp over the years 1991–2014 was taken as a benchmark for the on-farm wheat yields obtained with the field survey conducted during the growing season of 2020–2021. Despite the temporal mismatch between Yp and Ya data, the average Yp values adopted here can be considered reliable due to low inter-annual Yp variability in Northwest India. For each field in the database, the average Yp from the Global Yield Gap Atlas was retrieved using field-specific GPS coordinates and the technology yield gap was calculated as the difference between Yp and $Y_{HF}$.

### 2.3. Sustainability indicators

#### 2.3.1. Profitability

Profitability was estimated considering variable costs only, hence excluding costs of land and depreciation of machinery and other capital items. For this, the field-specific quantity of inputs, i.e., fertilizer, pesticide, labor, and seed, reported by the farmers were multiplied by their unit cost and the sum of these input-specific costs corresponded to the variable costs of each field. The average labor wage rates were asked to farmers and used in the estimation of labor cost. The labor used in each field was cross-checked against the total number of operations or amount used for each input. The costs associated with tillage operations were directly asked to farmers and were further triangulated against the number of tillage operations and diesel use. A flat rate of irrigation, which varied with the number of irrigations, was considered in the estimation of irrigation costs, as electricity is either free or partly subsidized in the states of Punjab and Haryana (Nayak et al., 2023).

The revenue from wheat production was calculated by multiplying the grain yield by the farm-gate price of wheat reported by the farmers. The Net Benefit Cost Ratio (NBCR) was calculated by dividing the revenue from wheat production with the respective variable cost as follows:

$$\mathrm{NBCRi} = \frac{Yi \times Wp - \sum_{i=1}^{n} XiPi}{\sum_{i=1}^{n} XiPi} \quad (4)$$

where $Xi$ refers to the amount of the $n$ inputs of irrigation water, fertilizer, pesticide, labor, tillage and seed in field $i$, $Pi$ is the respective price per unit of input, $Yi$ is the wheat grain yield, and $Wp$ is the farm-gate price of wheat.

#### 2.3.2. Nitrogen-use efficiency

The partial factor productivity of N (PFP-N), defined as the ratio of wheat yield to applied N, was the indicator considered to assess the N-use efficiency of wheat production (Table 1). This indicator captures a partial N balance as it does not consider indigenous soil N supply nor distinguishes between N recovery of applied N from conversion efficiency of N uptake (Dobermann, 2005). However, this is a widely used indicator in agronomic studies (e.g., Cassman et al., 2002; Nayak et al., 2022), providing a first-order assessment of N-use efficiency in farmer field data with minimal assumptions.

#### 2.3.3. Greenhouse gas emissions

The "Mitigation Options Tool" developed by the CGIAR research

**Table 1**
Descriptive statistics of the key management practices and key performance indicators of wheat production in NW-IGP.

| | Mean | Standard deviation | Minimum | Maximum |
|---|---|---|---|---|
| Sowing date in Julian dates | 311.9 | 6.1 | 292.0 | 339.0 |
| Fallow duration in days | 16.9 | 8.3 | 0.0 | 33.0 |
| Seed rate (kg/acre) | 44.7 | 4.2 | 35.0 | 60.0 |
| N applied (kg/ha) | 161.8 | 17.3 | 90.1 | 227.0 |
| P applied (kg/ha) | 65.1 | 11.4 | 0.1 | 97.8 |
| Cost of cultivation (INR/ha) | 28570.0 | 2508.0 | 20928.9 | 36025.0 |
| Gross return (INR/ha) | 88758.4 | 8924.2 | 55493.2 | 118696.8 |
| Net return (INR/ha) | 60188.3 | 9139.6 | 27931.8 | 87000.0 |
| Net benefit cots ratio | 2.1 | 0.4 | 0.9 | 3.2 |
| Wheat yield (kg/ha) | 4912.0 | 509.9 | 3032.4 | 6521.8 |
| Global warming potential (Kg co2-eq/ha) | 1384.1 | 529.1 | 62.0 | 2379.8 |
| Partial factor productivity of N | 41.6 | 9.2 | 21.2 | 86.0 |
| **Categorical variables (Number of data points in braces)** | | | | |
| Residue maintain | Yes (2524); No (1403) | | | |
| Tillage in rice | < =4 (1047); > =7 (859); 5 (1305); 6 (716) | | | |
| Lodging | Yes (1446); No (2481) | | | |
| Tillage in wheat | Intensive (1119); Moderate (1230); ZT/MT (1578) | | | |
| Crop establishment method | Broadcasting (1879); Line sowing after tillage (507); Super seeder (547); Zero tillage sowing (994) | | | |
| Irrigation in wheat | < =3 (2891); > =4 (1036) | | | |
| Weed severity | Low (1413); Medium (2514) | | | |
| Insect severity | None (1327); Low (1299); Medium (1301) | | | |
| Disease severity | None (1270); Low (1444); Medium (1213) | | | |

program on Climate Change Agriculture and Food Security (CCAFS-MOT; Feliciano et al., 2017) was used to estimate GHG emissions, and related carbon footprint, of wheat production. The CCAFS-MOT uses a combination of empirical models to quantify GHG emissions in agricultural production systems. In doing so, the tool considers factors like land use change over the past two decades, nitrous oxide ($N_2O$) emissions associated with the use of mineral fertilizers and manure application (based on soil organic carbon, soil pH, soil texture, climate, crop type, and length of the experiment), carbon dioxide ($CO_2$) emissions from mineral fertilizer production, and GHG emissions from crop residue burning and farm energy use.

The tool calculates background and fertilizer induced GHG emissions based on a multivariate empirical model (Bouwman et al., 2002) for $N_2O$ and nitric oxide (NO) emissions, and the model of FAO/IFA (2001) for ammonia ($NH_3$) emissions. GHG emissions from crop residues returned to the field were calculated using IPCC $N_2O$ Tier 1 emission factors. Similarly, GHG emissions from the production and transportation of mineral fertilizers were based on the Ecoinvent database (https://ecoinvent.org). GHG emissions from changes in soil carbon due to tillage, manure, and residue management were estimated using the IPCC methodology (see Ogle et al., 2005, and Smith et al., 1997). GHG emissions of $CO_2$ due to urea application were also estimated using the IPCC methodology (IPCC et al., 2006).

To estimate the total GHG emissions for each field, i.e., the global warming potential, all GHG emissions were converted to $CO_2$-equivalents ($CO_2$ eq) using the global warming potential (over 100 years) of 28 and 265 for $CH_4$ and $N_2O$, respectively. Although CCAFS-MOT does not capture the soil dynamics associated with those emissions, it is still a useful tool for a first order assessment of GHG emissions and for planning emission reductions specific to each field.

### 2.4. Multicriteria assessment

The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) (Hwang and Yoon, 1981) was used to assess the sustainability of wheat production according to actual yield, NBCR, PFP-N, and GHG emissions. This technique ranks observation units from most efficient (i.e., close to the ideal solution) to least efficient (furthest from the ideal solution) according to different indicators and user-defined weights for each indicator.

TOPSIS is implemented in three steps. First, indicator values are standardized to a common scale, viz. $n_{ij} = x_{ij}/\sqrt{\sum_{i=1}^{m} x_{ij}^2}$, where $i$ refers to number of $m$ observation units (fields in our dataset), and $j$ the number of indicators considered in the analysis. The normalized indicator values ($n_{ij}$) are then multiplied by user-defined weights for the relative importance of each indicator ($w_j$), to derive the weighted indicator score ($v_{ij}$). Secondly, positive and negative ideal solutions are identified, and their minimum and maximum values are determined for each indicator. A higher number is better for a positive ideal solution (e.g., yield) and a lower number is better for a negative ideal solution (e.g., GHG emissions). Finally, for each observation unit, the distance from the positive ideal solution and from the negative ideal solution is computed in a $j$ dimensional space, where $j$ is the number of indicators considered in the assessment. The TOPSIS score indicates how far each observation unit is from the negative ideal solution in comparison to the total distance from the positive and the negative ideal solutions. An observation unit with a larger distance from the negative ideal solution is close to the positive ideal solution and thus has a larger TOPSIS score as well as rank. The *topsis()* function from 'topsis' R package (Yazdi, 2013) was used to calculate the distance scores and delineate the field ranks for the scenarios explained below.

TOPSIS was used to obtain the rank of each field for five different scenarios. The first scenario considered the four indicators equally important, assigning equal weights to all indicators. The second scenario prioritized wheat yield over all other indicators, assigning it a weight five times greater than the other indicators, reflecting a production-maximizing situation. The third scenario explored how economic maximization affected the field ranks by considering the NBCR as the most important indicator (i.e., the weight of NBCR was five times that of the other indicators). The fourth and fifth scenarios focused on prioritizing environmental sustainability over other dimensions by considering minimization of GHG emissions and maximization of PFP-N as the most important indicators, respectively, again defining the weight of the respective indicator as five times that of the other indicators. With this assessment, we identified the fields performing best under different production objectives and assessed synergies and trade-offs in performance for different groups of fields. Fields were classified into four groups based on their rankings under each of the five scenarios. 'Most efficient fields' were defined as those having a TOPSIS rank score above the 75 % quantile of the distribution of all TOPSIS rank scores. Similarly, fields with TOPSIS scores between the 50th and 75th, 25th and 50th, and 0th and 25th percentiles of the distribution of all TOPSIS rank scores were classified as 'efficient,' 'less efficient,' and 'least efficient' fields, respectively. Boxplots of the four indicators were developed for each group of fields (i.e., from most to least efficient) in each scenario to characterize the variability in each indicator for the different groups of fields. The *lm()* function in R was used to fit linear regressions between all indicators across different field groups and to quantify synergies and trade-offs under the first scenario of equal weight for all indicators.

### 2.5. Random forest and variable importance

A random forest classification model was used to identify the important management practices governing the field classification obtained from TOPSIS under the scenario of equal weight for the four indicators. A total of 19 management variables were considered in this analysis, including the number of tillage operations for rice and wheat (two separate variables), residue management, crop establishment method, sowing date, seed rate, variety type, number of irrigations, amounts of N and P applied, severity of weeds, diseases, and pests, weed control method, herbicide, fungicide, and insecticide applications, timing of the first herbicide application, and crop lodging severity. These management variables were identified from a fine-tuned random forest model fitted to explain yield variability using the same dataset (Nayak et al., 2022a). The selected variables are agronomically meaningful and the result of recursive feature elimination prior to fitting machine learning models. The effect of the most important variable, as identified by the variable importance plot, was analyzed using descriptive statistics (i.e., the proportion of fields in each group reporting a specific management practice). The *randomForest()* function from 'randomForest' R package (Breiman, 2001; Liaw and Wiener, 2002) was used to construct the classification model. The *varImp()* function was used to identify the important variables. The field classification error was evaluated using a permutation-based approach, measuring how many fields were misclassified when the values of a variable were randomly shuffled.

## 3. Results

### 3.1. Yield gaps and drivers of yield variability

Wheat Ya in Northwest India was on average 4.9 t ha$^{-1}$, corresponding to 67 % of Yp (Fig. 1). Ya was highest in Karnal and Kurukshetra (ca. 75 % of Yp) and lowest in Ambala (ca. 61 % of Yp; Fig. 1). The efficiency, resource, and technology yield gaps were on average 0.45, 0.40, and 1.5 t ha$^{-1}$, respectively, across the surveyed districts (Fig. 1A). Efficiency and resource yield gaps accounted for ca. 12 % of Yp, whereas the technology yield gap accounted for 21 % of Yp.

The gamma value of the fitted Cobb-Douglas production function indicates a greater contribution of random errors associated with technical efficiency ($u_i$) than random errors associated with random noise ($v_i$) to the overall model results (Table 2). Sowing date had the largest significant negative effect on wheat yield with a 1 % increase in sowing date resulting in 1.3 % decline in wheat yield (Table 2). Conversely, the average seasonal minimum temperature had the largest significant positive effect on wheat yield. Moreover, a 1 % increase in N applied was associated with a 0.14 % increase in wheat yield, whereas a 1 % increase in total crop duration was associated with a 0.6 % decline in wheat yield. The number of tillage operations for the previous rice crop had a significant negative effect on wheat yield, whereas zero or minimum tillage prior to wheat sowing increased wheat yield compared to intensive tillage. Residue retention also showed a significant positive effect on wheat yield, although the effect was small (Table 2). Parameter estimates, and respective significance, were consistent between Cobb-Douglas models fitted with and without inefficiency effects (Table 2). The timing of the 1st and 2nd urea topdress application had a significant effect on the efficiency yield gap, with later dates of the 1st topdress of urea resulting in larger efficiency yield gaps whereas the opposite was observed for the 2nd topdress of urea (Table 2).

### 3.2. Sustainability indicators and their relationship

The mean wheat yield across the surveyed districts ranged from 4.3 to 5.2 t ha$^{-1}$, being highest in Karnal and Kurukshetra and lowest in Ambala (Fig. 2A). PFP-N was highest in Karnal, Kurukshetra, and Ambala with an average 45–48 kg grain kg$^{-1}$ N applied (Fig. 2B). Conversely, the lowest PFP-N was observed in Ludhiana, Patiala, and Kapurthala with an average of 35 kg grain kg$^{-1}$ N applied. The lowest values of PFP-N varied across districts, between 21 and 31 kg grain kg$^{-1}$ N applied, while the largest PFP-N varied between 53 and 86 kg grain kg$^{-1}$ N applied (Fig. 2B). NBCR was largest in Karnal (mean of 2.3 USD USD$^{-1}$) and lowest in Ambala (1.7 USD USD$^{-1}$; Fig. 2C). Yet, there were no large differences in NBCR across districts, except for Ambala, with mean values between 2.0 and 2.5 USD USD$^{-1}$. The largest GHG emissions were observed in Kurukshetra, with an average of 1763 kg $CO_2$ eq ha$^{-1}$ and a range between 450 and 2380 kg $CO_2$ eq ha$^{-1}$ (Fig. 2D). The lowest GHG emissions were observed in Kapurthala, with an average of 889 kg $CO_2$ eq ha$^{-1}$ and a range between 500 and 1500 kg $CO_2$ eq ha$^{-1}$ (Fig. 2D). The minimum GHG emissions varied between 62 and 450 kg $CO_2$ eq ha$^{-1}$ across districts, whereas the maximum GHG emissions varied between 1950 and 2380 kg $CO_2$ eq ha$^{-1}$ (Fig. 2D).

Synergies and trade-offs between indicators were quantified for the different group of fields under the scenario considering equal weights for all indicators (Fig. 3). NBCR increased linearly with increases in wheat yield for all field groups (Fig. 3A), indicating a synergy between wheat yield and profitability. The intercept was higher for the most efficient fields than for less efficient fields and an intermediate intercept was observed for efficient and less efficient fields. Yet, the slope of the regression was similar for all field groups. Therefore, profitability for a given yield level was higher for most efficient fields than for the other field groups. Conversely, there was a different relationship between wheat yield and GHG emissions (Fig. 3B) and NBCR and GHG emissions (Fig. 3D). The steepest decline in GHG emissions per ton of grain was observed for the efficient fields, followed by the less efficient and most efficient fields: for a 5 t ha$^{-1}$ wheat yield, most efficient fields had an

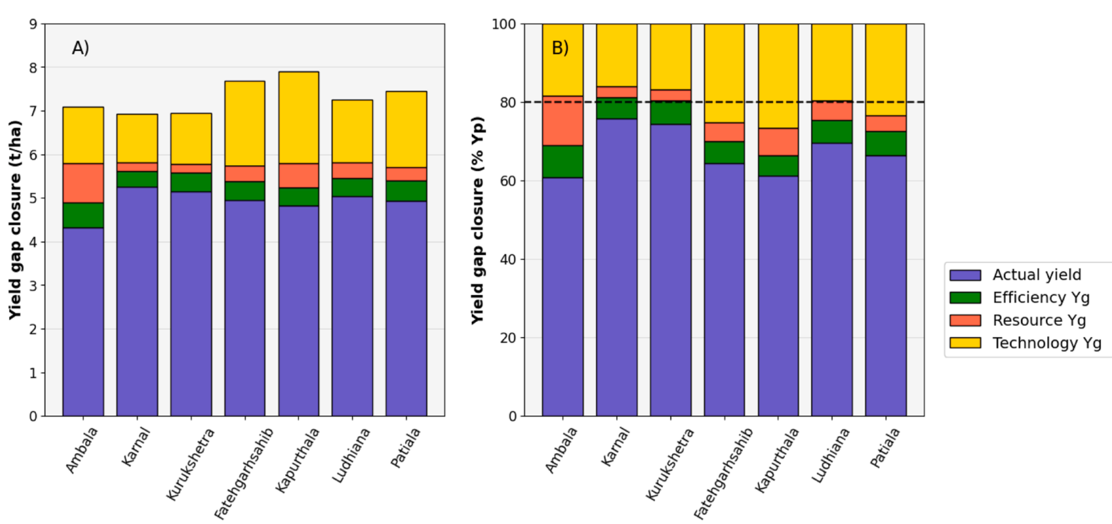


**Fig. 1.** Wheat yield gap decomposition into efficiency, resource, and technology yield gaps for the state of Haryana (Ambala, Karnal and Kurukshetra) and Punjab (Fatehgarh Sahib, Kapurthala, Ludhiana and Patiala) in the Northwestern Indo-Gangetic Plains of India during the 2020–2021 winter growing season. Panel (A) and (B) show yields and yield gaps in absolute (t ha$^{-1}$) and relative terms (% of Yp), respectively. Yield gap closure refers to the ratio between actual farmers' yields (Ya) and simulated potential yields (Yp).

**Table 2**
Parameter estimates of the stochastic frontier models fitted for wheat production systems in the Northwestern Indo-Gangetic Plains of India during the winter growing season of 2020–2021.

| Variables | Cobb-Douglas without inefficiency effects | Cob-Douglas with inefficiency effects |
|---|---|---|
| **Production function** | | |
| (Intercept) | 0.036 * ** | 0.015 * |
| Maximum temperature (°C) | 0.137 | −0.046 |
| Minimum temperature (°C) | 0.534 * ** | 0.655 * ** |
| Precipitation (mm) | 0.026 | 0.016 |
| Total N applied (kg ha$^{-1}$) | 0.146 * ** | 0.144 * ** |
| Total $P_2O_5$ applied (kg ha$^{-1}$) | 0.017 * ** | 0.012 * |
| Seed rate (kg ha$^{-1}$) | 0.082 * ** | 0.060 * ** |
| Sowing dates in Julian days | −1.262 * ** | −1.144 * ** |
| Crop duration (days) | −0.600 * ** | −0.473 * ** |
| Herbicide applied (ai ai$^{-1}$) | 0.025 * ** | 0.025 * ** |
| Fungicide applied (ai ai$^{-1}$) | −0.002 * * | −0.001 |
| Insecticide applied (ai ai$^{-1}$) | −0.004 * * | −0.006 * ** |
| Irrigation number (>=4) | 0.029 * ** | 0.024 * ** |
| Tillage intensity in rice (>=7) | −0.026 * ** | −0.024 * ** |
| Tillage intensity in rice (5) | −0.002 | 0.001 |
| Tillage intensity in rice (6) | 0.011 * | 0.011 * |
| Residue retention (Yes) | 0.029 * ** | 0.028 * ** |
| Tillage intensity in wheat (Moderate) | 0.012 * * | 0.009 * |
| Tillage intensity in wheat (ZT or MT) | 0.023 * ** | 0.017 * ** |
| Texture category (Moderate) | 0.018 * ** | 0.022 * ** |
| Weed severity (Medium) | −0.001 | 0.001 |
| Lodging category (Yes) | −0.006 # | −0.002 |
| **Inefficiency effects** | | |
| (Intercept) | | −0.323 * |
| Days of 1st urea top dressing | | 1.452 * ** |
| Days of 2nd urea top dressing | | −1.863 * ** |
| 1st herbicide application time | | −0.004 |
| **Model evaluation** | | |
| SigmaSq ($\sigma^2$) | 0.017 * ** | 0.034 * ** |
| Gamma (γ) | 0.786 * ** | 0.877 * ** |

average GHG emission of ca. 750 kg $CO_2$ eq ha$^{-1}$, followed by efficient fields with ca. 1300 kg $CO_2$ eq ha$^{-1}$, less efficient fields with ca. 1650 kg $CO_2$ eq ha$^{-1}$, and least efficient fields with ca. 1850 kg $CO_2$ eq ha$^{-1}$ (Fig. 3B). Moreover, GHG emissions decreased by only 12 % with reductions in wheat yield, from 5.7 to 3.0 t ha$^{-1}$, for the least efficient fields, but by 73 % with reductions in wheat yield, from 6.5 to 3.9 t ha$^{-1}$, for most efficient fields. Similar relationships and trade-offs were observed between GHG emissions and NBCR (Fig. 3D) as that of GHG emission and yield, due to the linear relationship between wheat yield and NBCR (Fig. 3A). Finally, the regression between wheat yield and PFP-N and between NBCR and PFP-N had a positive slope of similar magnitude for most efficient, efficient, less efficient, and least efficient fields (Figs. 3C and 3E). Yet, for a given wheat yield and NBCR, most efficient fields had a lower PFP-N than the other field groups (Fig. 3C). The relationship between PFP-N and GHG emissions was also positive for all field groups, but most efficient fields attained higher PFP-N per unit of GHG emissions than the other groups (Fig. 3F). Conversely, least efficient fields exhibited high levels of GHG emissions (1700–2000 kg $CO_2$ eq ha$^{-1}$) and low PFP-N (30–45 kg grain kg$^{-1}$ N; Fig. 3F).

In summary, it is possible to produce wheat sustainably in Northwest India as most efficient fields achieved high wheat yield and economic benefit with the lowest GHG emissions, and with only slightly lower PFP-N than the other field groups. Yet, this is not true for the efficient and less efficient fields. The management practices in most efficient fields can be assumed optimal, hence the trade-off between yield and GHG emissions for this field group is likely hard to overcome with current practices. We also observed a trade-off between wheat yield and GHG emissions across the most efficient, efficient, and less efficient field groups given their current practices. For these field groups, an increase in wheat yield consistently increased GHG emissions. However, for the least efficient fields, we observed no trade-off between wheat yield and GHG emissions, suggesting opportunities to increase productivity in this group of fields without additional GHG emissions. Despite within group synergies and trade-offs, the performance of efficient, less efficient, and least efficient fields could be further improved with practice change, i.e., pathways for them to transition towards the sustainability performance observed in most efficient fields. Our results thus show clear, group-specific, pathways to achieve sustainable wheat production at the regional level.

### *3.3. Field classification under different scenarios*

The performance of the different farm-fields was affected by different optimization scenarios prioritizing specific dimensions of sustainability (Fig. 4). Yet, these effects were more noticeable for most and least efficient fields than for efficient and less efficient fields. Therefore, the results described below focus on differences in performance for most and least efficient fields under different scenarios.

Most efficient fields in the maximum yield scenario attained on average 10 % higher yield than the same group of fields in the maximum PFP-N and minimum GHG emissions scenarios (Fig. 4A). The average yield for most efficient fields was nearly similar for the maximum yield, maximum NBCR, and equal weight scenarios. Conversely, least efficient fields had 13 % lower yield in the maximum yield scenario compared to the minimum GHG emissions and maximum PFP-N scenarios (Fig. 4A). No major differences in yield were observed for least efficient fields under the equal weight, maximum yield, and maximum NBCR scenarios. Similar to the maximum yield scenario, most efficient fields in the maximum NBCR scenario had a higher NBCR than most efficient fields in the minimum GHG emissions and maximum PFP-N scenarios, whereas the opposite was true for least efficient fields (Fig. 4B).

Most efficient fields in the minimum GHG emissions scenario had 64, 53, 50 and 25 % lower GHG emissions than most efficient fields in the maximum PFP-N, maximum yield, maximum NBCR, and equal weight scenarios, respectively (Fig. 4C). Conversely, least efficient fields in the minimum GHG emissions scenario had similar GHG emissions to the least efficient fields under the maximum PFP-N scenario, and 27 and 40 % lower GHG emissions than least efficient fields in the maximum NBCR and maximum yield scenarios, respectively (Fig. 4C). The average PFP-N for most efficient fields in the maximum PFP-N scenario was 53 kg grain kg$^{-1}$ N applied (Fig. 4D). Most efficient fields in the maximum yield, minimum GHG emissions, and maximum NBCR scenarios had 18, 40, and 21 % lower PFP-N than most efficient fields in the maximum PFP-N scenario, respectively (Fig. 4D). Finally, average PFP-N for least efficient fields in the maximum PFP-N scenario was about 30 kg grain kg$^{-1}$ N applied and slightly greater, about 40 kg grain kg$^{-1}$ N applied, in the other scenarios (Fig. 4D).

### *3.4. Management practices contributing to sustainable and cleaner production*

The most important crop management practices affecting the field classification in the random forest model were (a) tillage intensity for

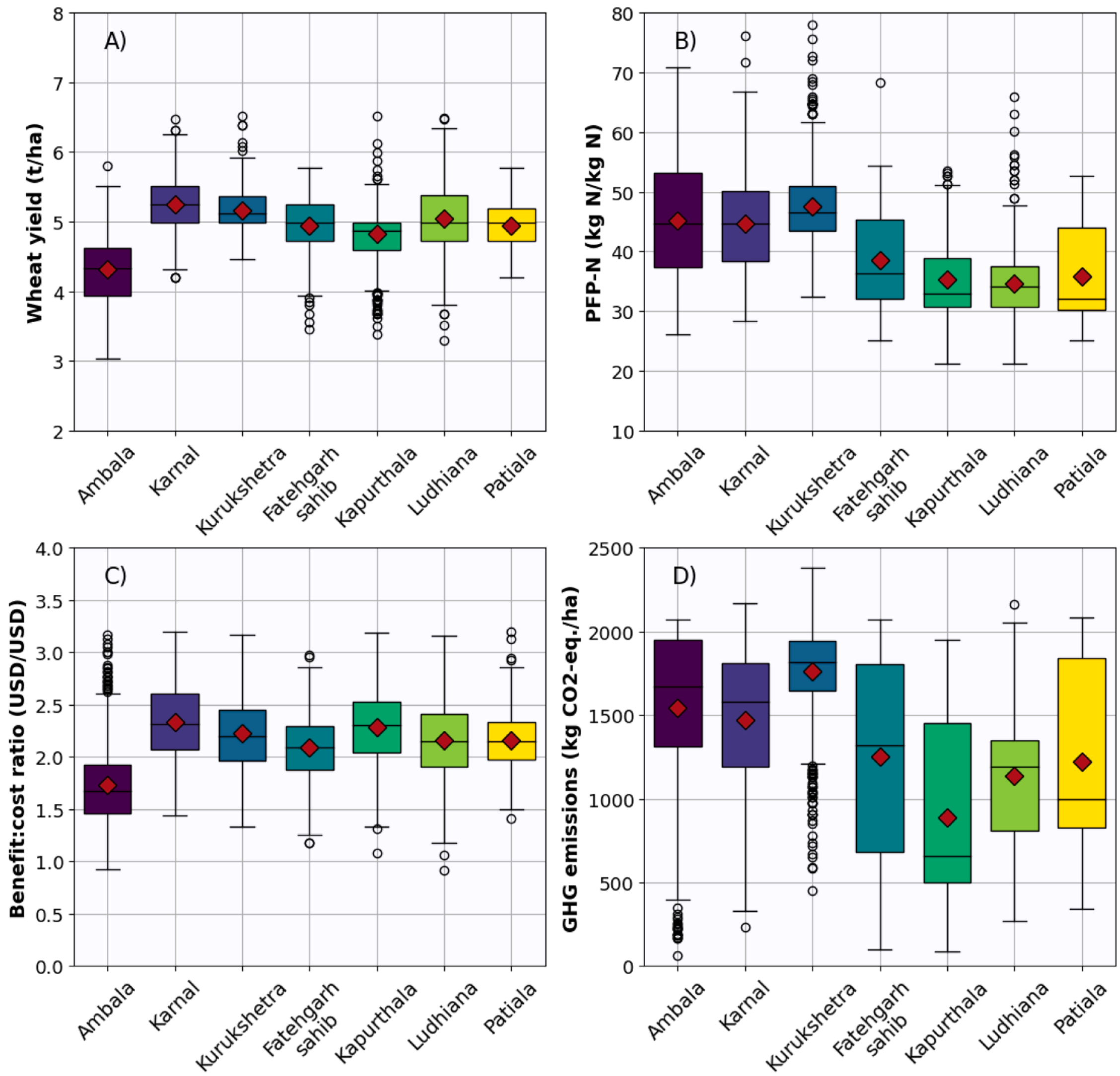


**Fig. 2.** On-farm variability of sustainability indicators for wheat production in the Northwestern Indo-Gangetic Plains of India: wheat yield (A), N partial factor productivity (B), net benefit cost ratio (C), and greenhouse gas (GHG) emissions (D). Ambala, Karnal, and Kurukshetra are districts in the state of Haryana, whereas Fatehgarh Sahib, Kapurthala, Ludhiana, and Patiala are districts in the state of Punjab. Red diamonds indicate the mean of each sustainability indicator in each district.

wheat for the scenario with equal weights for all indicators, (b) tillage intensity for the preceding rice crop for the yield maximization scenario, (c) wheat establishment method for profit maximization scenario, and (d) residue management prior to wheat establishment for the minimum GHG emissions and maximum PFP-N scenarios (Fig. 5). N fertilizer applied was the second most important variable to explain the field classification for the equal weights and maximum PFP-N scenarios, and the third most important variable for the minimum GHG emissions scenario. Residue management was the second most important variable for the yield maximization scenario, whereas herbicide use and tillage intensity prior to wheat establishment were the second most important variables for profit maximization and minimum GHG emissions scenarios, respectively.

The effect of the most important management practices on the field classification was further analyzed (Fig. 6). In the scenario with equal weights across indicators, where tillage intensity in wheat was the most important variable in the random forest model, 82 % of the most efficient fields used zero or minimum tillage, compared to 55 % of the least efficient fields, which reported intensive tillage for wheat (Fig. 6A). For the yield maximization scenario, very high tillage intensity for the previous rice crop was associated with poor performance in wheat. Nearly half of the least efficient fields in the yield maximization scenario reported more than seven tillage operations for the previous rice crop, whereas ca. 65 % of the most efficient fields reported five or less tillage operations for the previous rice crop (Fig. 6B). For the profit maximization scenario, broadcasting wheat was the preferred crop establishment method for about 55 % and line sowing after tillage for about 25 % of the least efficient fields (Fig. 6C). Conversely, a large share of most efficient fields in the profit maximization scenario reported zero tillage methods for wheat establishment (Fig. 6C). Regarding the minimum GHG emissions scenario, nearly 90 % of the efficient fields reported crop residue retention prior to wheat establishment, as opposed to nearly 80 % of the least efficient fields, for which residue removal was reported (Fig. 6D). Finally, crop residue retention and N fertilizer applied were important drivers of field classification in the PFP-N maximization scenario. Yet, the effect of residue retention on PFP-N was negative with nearly 75 % of the most efficient fields reporting residue removal and nearly all the least efficient fields reporting residue retention.

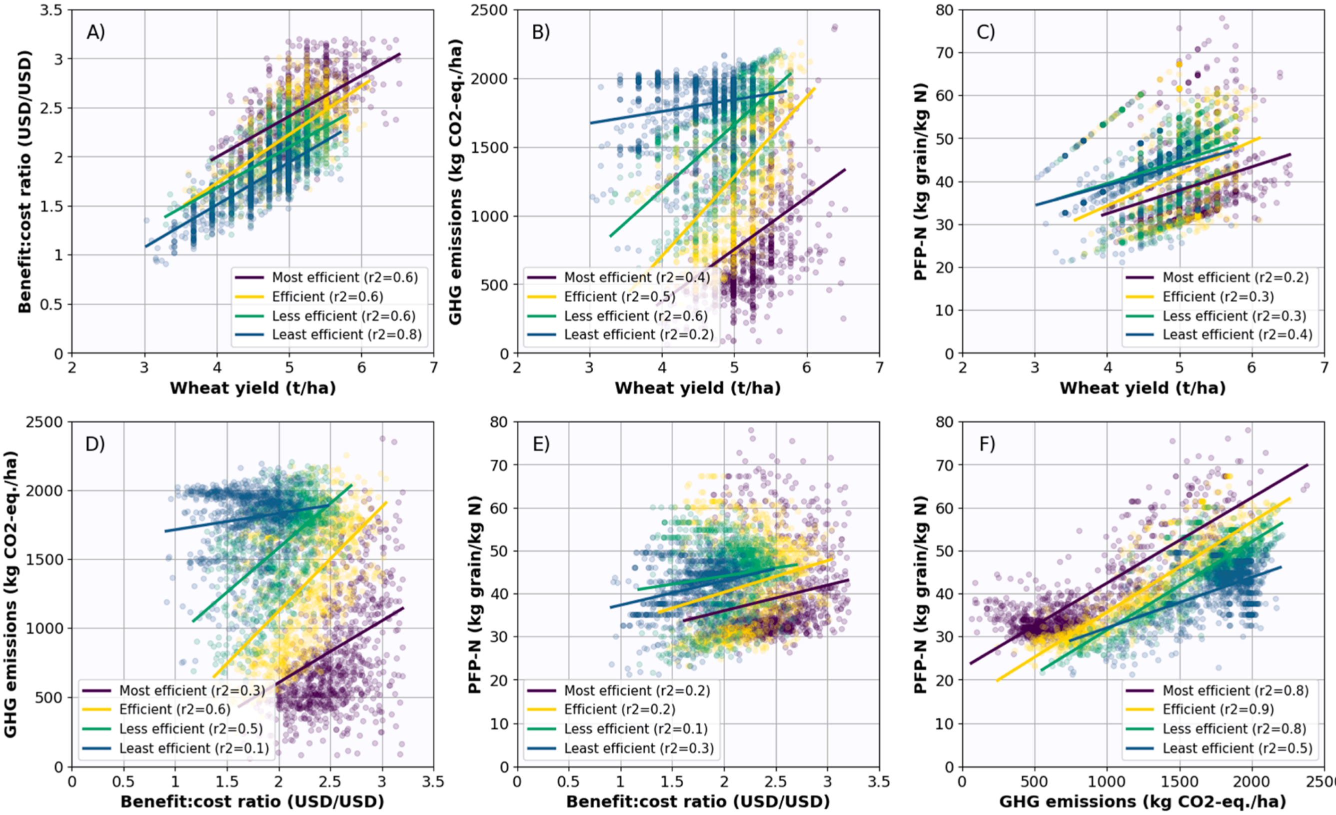


**Fig. 3.** Relationship between four sustainability indicators for wheat production in the Northwestern Indo-Gangetic Plains of India. Linear regressions were fitted for different groups of fields (most efficient, efficient, less efficient, and least efficient) derived using TOPSIS under the assumption of equal weight between all the indicators. The $R^2$ of the fitted linear regressions is shown in the legend of each panel.

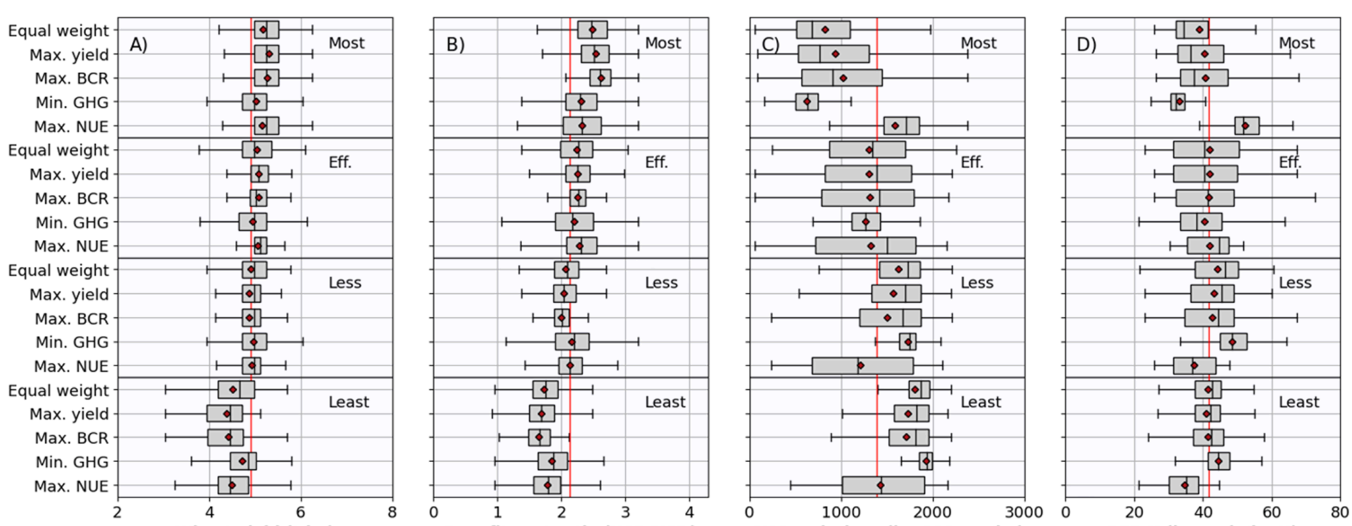


**Fig. 4.** Impact of five scenarios on wheat yield (A), net benefit cost ratio (B), greenhouse gas emissions (C), and N partial factor productivity (D) for most efficient, efficient, less efficient, and least efficient fields. The five scenarios were implemented with TOPSIS assuming equal weight for all four sustainability indicators (equal weight), maximum yield (max. yield), maximum net benefit cost ratio (max. BCR), minimum greenhouse gas emissions (min. GHG), and maximum N partial factor productivity (max. NUE). Red diamonds show the mean value of each indicator for each farm-field group x scenario combination and vertical red lines show the mean value of each indicator for the pooled data.

## 4. Discussion

### *4.1. Sustainable and cleaner wheat production in Northwest India*

The Punjab and Haryana states of Northwest India are popularly known for ensuring food security to the country and renowned for high productivity levels (Chauhan et al., 2012). Similar to previous findings for rice (Nayak et al., 2022), the small wheat yield gaps estimated in this study confirm the high productivity of rice and wheat crops in the region. Currently, wheat farms in Northwest India achieve 60–75 % of the

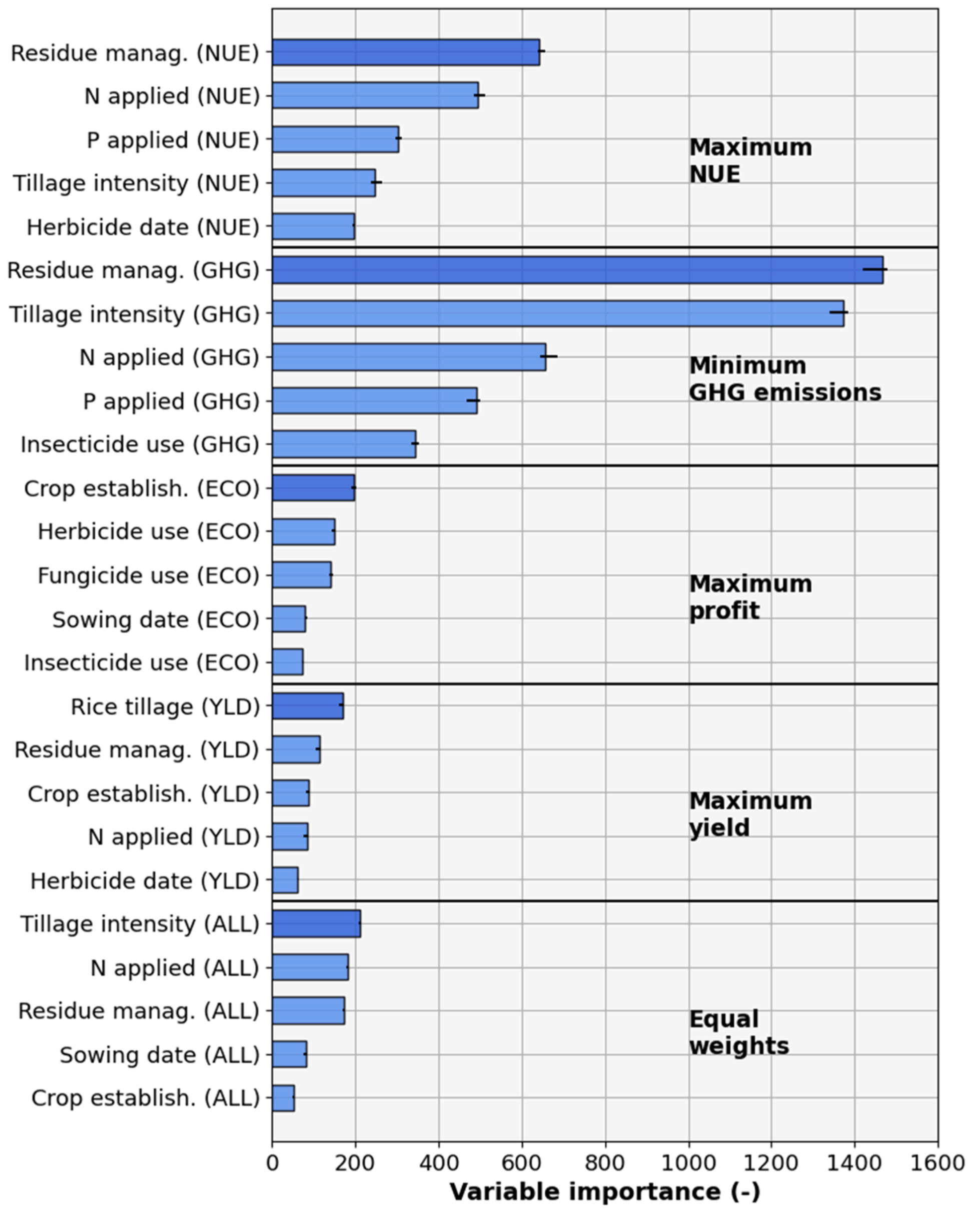


**Fig. 5.** Variable importance of random forest models fitted to the field classification derived with TOPSIS under five different scenarios: equal weights between all indicators (ALL), maximum wheat yield (YLD), maximum profitability (ECO), minimum greenhouse gas emissions (GHG), and maximum N-use efficiency (NUE).

potential yield. The small yield gap was mostly attributed to the technology yield gap (ca. 20 % of Yp, corresponding to 1–2 t ha$^{-1}$), meaning that further increases in wheat production require precision agriculture technologies not yet widely used in farmers' fields. Yet, fine-tuning current practices, through narrowing efficiency and resource yield gaps, would increase wheat yield by ca. 0.9 t ha$^{-1}$, on average. Small yield gaps mostly attributed to the technology yield gap were also observed for rice crops in the same region (Nayak et al., 2022) and for arable crops, including wheat, in Northwest Europe (Silva et al., 2017). This situation contrasts with that in low-input settings, where narrowing efficiency and resource yield gaps could double wheat yields, with the technology yield gap accounting for as much as 50 % of the water-limited yield (Silva et al., 2021; Baudron et al., 2019). In production systems with high input use and limited potential for increasing farm yields, as demonstrated by this study, prioritizing resource-use efficiency becomes crucial (Kakraliya et al., 2022).

Multicriteria assessments of cropping systems (Davis et al., 2019) reveals trade-offs between different sustainability indicators (Struik et al., 2014), with the strength of the trade-off varying with the adopted management practices (Fig. 3). For instance, Sapkota et al. (2017) grouped farms in India based on yield and GHG emissions and evaluated the crop management practices (tillage intensity, residue management, and split N application) used by each group of farms. In another study, Ashok et al. (2021) observed trade-offs between energy use efficiency, GHG emissions, and resource-use efficiency in different geographies. Therefore, identifying which management practices perform best for different sustainability dimensions, and to quantify potential trade-offs between those different dimensions, is of utmost importance for high-input cropping systems as illustrated in this study for wheat crops in Northwest India. Despite the numerous approaches available for multicriteria assessment (Carof et al., 2013, Talukdar, 2016), TOPSIS was preferred due to its straightforward implementation to rank observation units based on weights assigned to different indicators (see also Özkan et al., 2019), hence allowing us to identify groups of fields with different performance under different scenarios.

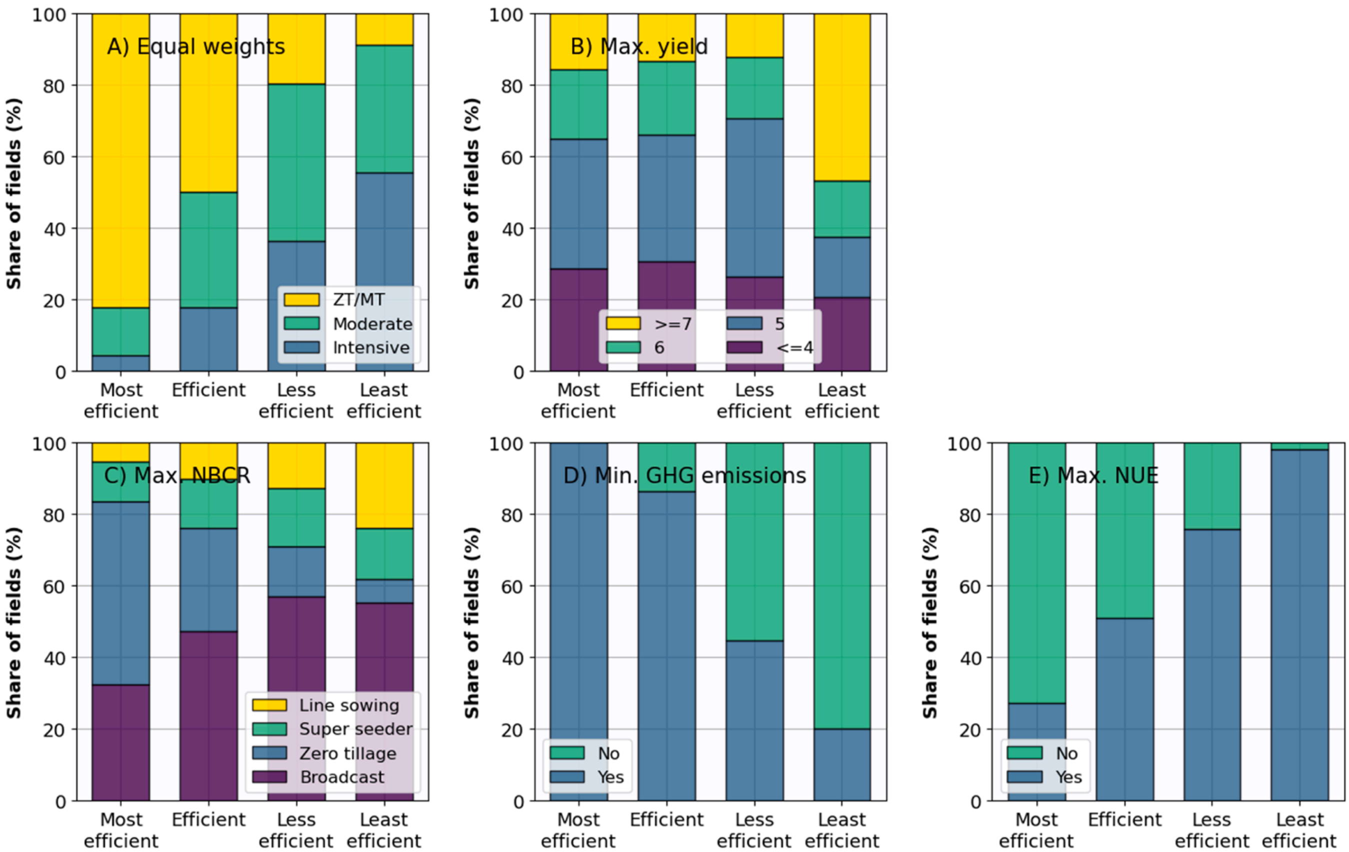


**Fig. 6.** Share of fields for the most important management practice explaining the TOPSIS farm-field classification under five scenarios: tillage practice for the scenario with equal weights for all the indicators (A), number of land preparation operations for the previous rice crop for the maximum yield scenario (B), crop establishment method for the maximum net benefit cost ratio scenario (C), residue retention for the minium greenhouse gas emissions scenario (D) or the maximum N-use efficiency scenario (E). Abbreviations: ZT/MT = zero tillage/minimum tillage.

### *4.2. Management drivers of field performance*

We found little evidence of trade-offs between wheat yield, profitability, and N-use efficiency in this study. This means that high wheat yields in Northwest India are compatible with increased profitability and nutrient-use efficiency (Figs. 3A and 3C), as also observed for other crops in other production systems (Silva et al., 2018, Silva et al., 2017). The latter was true when field performance was compared under a scenario assuming equal weights for all indicators (Fig. 3) and under scenarios prioritizing different indicators (Fig. 4). Yet, the relationship between the aforementioned indicators and GHG emissions was group-specific and hard to generalize. For instance, most efficient fields can achieve high productivity and profitability with low GHG emissions (Figs. 3A and 3B), even though GHG emissions increased with increasing levels of the other two indicators (Fig. 3B). This is a trade-off that seems hard to overcome with current farm practices. Two pathways for sustainable wheat production emerged: (1) least efficient fields can boost productivity and profitability without raising GHG emissions, and (2) fields of all efficiency levels can reduce GHG emissions to match those observed in the most efficient fields without sacrificing yield or profit. These pathways offer a promising approach to sustainable wheat production regionally.

Various management practices were identified as important drivers of the field classification under different scenarios (Fig. 5). For instance, tillage intensity for wheat and for the previous rice crop were important for the yield maximization scenario and for the scenario with equal weights for all indicators. Zero tillage practices reduce cultivation costs and increase profitability due to savings in tillage operations and hand-weeding (Sahoo et al., 2022; Samal et al., 2017). Moreover, zero tillage can also improve wheat yield and nutrient-use efficiency through timely planting and improvements in soil fertility (Aryal et al., 2015; 2022). Field experiments in the region further reported higher wheat yield followed by zero tillage rice production practices (Kumar et al., 2019), in agreement with our results. Conventional puddling of transplanted rice often causes the formation of a plow pan that restricts root development, whereas zero-tillage rice cultivation improves soil physical properties for subsequent crops (Gathala et al., 2011). Conversely, crop residue management was the most important practice governing the field classification in the minimum GHG emissions scenario. Residue retention is indeed a source of carbon to the soil, which can have a positive impact on crop yield and GHG emissions in the long run (Parihar et al., 2018; Jat et al., 2019a), particularly compared to residue burning. Finally, line sowing is known to improve crop establishment, and hence crop yield and profitability, which likely explains why it was identified as the most important practice governing the field classification in the profit maximization scenario. In conclusion, ensuring sustainable wheat production in Northwest India in the future requires due attention to crop management operations happening prior to or at planting, namely land preparation method, residue management, and crop establishment method. The evidence generated from the bottom-up approach, involving thousands of farms, aligns with the existing literature from the same region. The distribution of various management practices affects farm efficiency differently depending on which indicators are prioritized.

### *4.3. Methodological considerations*

We employed an innovative data-driven approach to assess farm performance in the context of sustainable and cleaner crop production. The four building blocks of our analysis were extensively applied in isolation in the past: stochastic frontier analysis to decompose yield gaps (cf. Silva et al., 2017), CCAFS-MOT to estimate GHG emissions from cropping systems (Sapkota et al., 2019), TOPSIS to conduct multicriteria assessments in agriculture (García-Cascales et al., 2021), and random forest to identify crop management determinants of crop yield variability (e.g., Nayak et al., 2022a). Yet, this is the first study combining all these methods to provide an integrated assessment of crop production with a case study for irrigated wheat in the Northwest India. With this data-driven integrated assessment, we were able to (1) quantify yield gaps and identify their causes, which is critical to delineate the scope for future yield increases, (2) cluster fields based on their performance according to four indicators, (3) quantify synergies and trade-offs between indicators for most efficient, efficient, less efficient, and least efficient fields, and finally (4) identify the management practices associated with each group of fields. Our approach builds entirely upon data-driven methods powered by a large database of farmer field data. It therefore depicts the sustainability of crop production under real farm conditions and guides future improvements attuned to the local context.

Multicriteria assessments are especially important for high productivity crops because small yield gaps often come at the expense of profitability and the environment (Silva et al., 2021). Expanding the methods used in this study to other high-input cropping systems would help quantify the sustainability of crop production at the farm and regional levels, targeting interventions contributing to sustainability improvements in those settings. The approach would also be useful for intermediate- and low-input cropping systems though, to characterize the current situation upon which the impact of different scenarios on key indicators could be explored *ex-ante*. Beyond applying the methodological approach to new environments and production systems, we also recommend that future studies explore the interactions between climatic conditions and crop management practices, and how this affects crop yield variability and the overall sustainability of the production system. Such analyses remain important to understand not only how crop production impacts the environment, but also how it benefits farmers and society at large.

## 5. Conclusion

This study aimed to quantify yield gaps and sustainability performance for irrigated wheat farms in Northwest India. Findings revealed that actual farm yields reach about 70 % of the potential yield, with current yield constraints associated with precision agricultural practices not used by farmers. A multicriteria assessment considering productivity, profitability, greenhouse gas emissions, and nitrogen-use efficiency unraveled that it is possible to produce wheat sustainably in Northwest India, without compromising current yields, and that two different strategies are required to achieve that at regional level. First, decreases in greenhouse gas emissions are possible for least efficient fields at same productivity level. Second, reductions in greenhouse gas emissions, to the levels observed for most efficient fields, seem possible for efficient, less, and least efficient fields without compromising wheat productivity and profitability. The trade-off observed for the most efficient fields between productivity and profitability on the one hand and greenhouse gas emissions on the other seems hard to overcome with current practices. Therefore, improving the performance of efficient, less efficient, and least efficient fields is paramount to improve the sustainability of wheat production in Northwest India in the future. Finally, the methodological approach deployed in this study was helpful to explore trade-offs between performance indicators and to identify the management practices that can deliver sustainable and cleaner crop production under on-farm conditions. It thus provides a blueprint for future integrated assessments of crop production built upon data-driven methods and powered by large databases of farmer field data.

## CRediT authorship contribution statement

**Hari Sankar Nayak:** Writing – review & editing, Writing – original draft, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **João Vasco Silva:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis. **C. M. Parihar:** Writing – review & editing, Writing – original draft, Supervision, Conceptualization. **Mangi Lal Jat:** Writing – review & editing, Supervision, Resources, Conceptualization. **Rajbir Singh:** Writing – review & editing. **Rakesh Kumar:** Writing – review & editing. **Deepak Ranjan Sena:** Writing – review & editing, Methodology, Formal analysis. **H.S. Jat:** Supervision. **H.S. Sidhu:** Supervision. **Timothy J. Krupnik:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Data curation, Conceptualization. **Tek B. Sapkota:** Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Funding acquisition, Formal analysis, Data curation.

## 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.

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## Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.eja.2024.127492.

## Data Availability

Data will be made available on request.

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