Field Crops Research 275 (2022) 108328

Contents lists available at ScienceDirect

Field Crops Research

journal homepage: www.elsevier.com/locate/fcr

Rice yield gaps and nitrogen-use efficiency in the Northwestern Indo-Gangetic Plains of India: Evidence based insights from heterogeneous farmers' practices

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ARTICLE INFO

Keywords:
Big data
Stochastic frontier analysis
Global yield gap atlas
Fertilizer management
Sustainability assessment

ABSTRACT

A large database of individual farmer field data (n = 4,107) for rice production in the Northwestern Indo-Gangetic Plains of India was used to decompose rice yield gaps and to investigate the scope to reduce nitrogen (N) inputs without compromising yields. Stochastic frontier analysis was used to disentangle efficiency and resource yield gaps, whereas data on rice yield potential in the region were retrieved from the Global Yield Gap Atlas to estimate the technology yield gap. Rice yield gaps were small (ca. 2.7 t ha$^{-1,}$ or 20% of potential yield, Yp) and mostly attributed to the technology yield gap (ca. 1.8 t ha$^{-1,}$ or ca. 15% of Yp). Efficiency and resource yield gaps were negligible (less than 5% of Yp in most districts). Small yield gaps were associated with high input use, particularly irrigation water and N, for which small yield responses were observed. N partial factor productivity (PFP-N) was 45–50 kg grain kg^{-1} N for fields with efficient N management and approximately 20% lower for the fields with inefficient N management. Improving PFP-N appears to be best achieved through better matching of N rates to the variety types cultivated and by adjusting the amount of urea applied in the 3rd split in correspondance with the amount of diammonium-phosphate applied earlier in the season. Future studies should assess the potential to reduce irrigation water without compromising rice yield and to broaden the assessment presented here to other indicators and at the cropping systems level.

1. Introduction

Rice contributes to about 30% of the calories consumed in India (Mohanty and Yamano, 2017) and is an important source of foreign exchange for the Government of India. India grows rice on about 43.8 million ha, with a total production of about 116 million tonnes per year (Government of India, 2019). Yet, rice cropped area in the country is predicted to decline by 6–7 million ha by 2050, because of climate change and conversion of agricultural land to other uses (Central Rice Research Institute, 2013). At the same time, consumer demand for rice is expected to rise from 114 to 137 million tons in the coming years (Central Rice Research Institute, 2013). As a consequence, rice production will need to increase by about 1.1% per year over the next four decades to ensure rice self-sufficiency at the national level (Gathala et al., 2013). The additional rice demand projected for the decades ahead must be met through increasing rice yields in low-yielding

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https://doi.org/10.1016/j.fcr.2021.108328
Received 29 June 2021; Received in revised form 16 September 2021; Accepted 14 October 2021
Available online 5 November 2021

regions, while maintaining current rice yields in high-yielding regions, as there is limited scope to bring additional land into cultivation. The maintenance of high-yielding areas must be achieved sustainably, as rice cultivation alone consumes approximately 80% of the energy and water used in Indian agriculture, and is responsible for 90% of the total greenhouse gas (GHG) emissions of all monsoon season cropped cereals (Davis et al., 2019).

The Northwestern Indo-Gangetic Plains (IGP) of India, which includes the states of Punjab and Haryana, account for approximately 25% of the country's total rice area. The dominant cropping system in the Northwestern IGP comprises a rice crop grown during the rainy season (or '*kharif*', between July and November) in rotation with a wheat crop during the winter season (or '*rabi*', between November to April), with land kept fallow between wheat harvest and rice planting. Rice is predominantly grown by transplanting seedlings into wet-tilled puddled soil and the field is kept flooded for most of the growing season. The high rice yields in the states of Punjab and Haryana are the result of adoption of improved varieties, intensive use of irrigation water and fertilizers, and the expansion of irrigated areas (Mohanty and Yamano, 2017). The latter were largely encouraged through government subsidies on electricity and fertilizer N, coupled with market guarantee of paddy purchase through minimum support prices. For instance, farmers in the states of Punjab and Haryana on average use 1,320 and 1,800 mm of irrigation water, respectively, for rice cultivation (Sharma et al., 2018), despite these being water-scarce regions. These two states use nearly 30% of total electricity consumption in the agricultural sector (Sharma et al., 2018). The overexploitation of groundwater resources for irrigation, a decline in the response to applied fertilisers, the emergence of micronutrient deficiencies and herbicide resistant weeds, and increasing pressure from pests and diseases have raised concerns about the sustainability and profitability of rice production in the Northwestern IGP of India (Bhatt et al., 2016, 2021).

Sustainable intensification aims to narrow yield gaps on existing agricultural land while increasing resource-use efficiencies and minimizing environemntal externalities (Silva et al., 2021b, Cassman and Grassini, 2020). Yield gaps are defined as the difference between potential and actual yields for irrigated crops (van Ittersum et al., 2013), with the magnitude of the gap providing a metric for how efficiently land is used under on-farm conditions. Potential yield (Yp) is defined as the yield of a crop cultivar when grown with water and nutrients non-limiting and biotic stresses effectively controlled, whereas actual yield (Ya) refers to the yield observed in farmers' fields subject to water and nutrient limitations, and to reductions by pests, diseases and weeds (van Ittersum and Rabbinge, 1997). Identifying the causes behind existing yield gaps can aid in the development of more appropriate soil and crop management advisory systems, which, if designed with on-farm data and through farmer participation, may be more commensurate with farmers' objectives and constraints (Silva et al., 2017a, 2017b; Rattalino-Edreira et al., 2018; Prasad et al., 2017). Yield gap assessments are also helpful to inform the scope for sustainable intensification at local level (Silva et al., 2021b; Stuart et al., 2016, Lobell et al., 2009).

Understanding the drivers behind yield gaps and the opportunities to increase crop yield, or reduce inputs without compromising crop yield under on-farm rather than experimental settings, requires a wealth of individual farmer field data with detailed biophysical and crop management information (Beza et al., 2017). Such data are becoming increasingly available across farming systems around the world (Silva et al., 2020; Rattalino-Edreira et al., 2018). When combined with secondary biophysical data, such detailed information can be used to infer the performance of multiple genotypes and their interactions with environmental and management factors. Such analyses can be comparable to running thousands of field experiments, and can aid in the identification of best-bet management options in a given biophysical unit, in a cost-effective way (Rattalino-Edreira et al., 2018). The latter is crucial to accelerate the sustainable intensification of current cropping systems and to design research and development programs supporting progress towards the application of improved management practices that reduce yield gaps while improving resource-use efficiency in farmers' fields.

The objective of this study was two-fold: (1) to decompose rice yield gaps into efficiency, resource, and technology yield gaps, and (2) to assess the scope to reduce input use while maintaining current rice yields at the regional scale in the Northwestern IGP of India. We hypothesized that rice yield gaps in this region are relatively small (i.e., 20–30% of Yp), due to the intensive use of inputs, and that input use (particularly irrigation water and N) could be reduced without compromising crop productivity. Our analysis builds upon a large database (n = 4,107 fields) of crop management practices reported by individual farmers collected during the 2020 *kharif* season in the states of Punjab and Haryana. Our study provides both evidence of, and a methodology for, the quantification of yield gaps and the identification of approaches to increase resource-use efficiency. This approach represents a potential alternative to manipulative experimentation that could be reproduced in different cropping systems and environmental contexts

2. Materials and methods

2.1. Database of farmer field data

2.1.1. Field survey and primary data collection

A field survey was conducted by the Indian Council of Agricultural Research – Central Soil Salinity Research Institute (ICAR-CSSRI), the Bourlag Institute for South Asia (BISA) and the International Maize and Wheat Improvement Centre (CIMMYT) during the 2020 *kharif* (rainy) season across rice fields in the states of Punjab and Haryana (Fig. 1). Haryana and Punjab are the two most important states for rice production in the Northwestern IGP and are comprise of arid environment with saline soil in some parts of Haryana. The surveyed districts in Punjab lie on the central plain agro-climatic zone characterized by a semi-arid to dry subhumid climate, with a mean annual temperature of 23.3–25.8 °C and an average rainfall of 600mm (70% of which is typically received during monsoon season that spans from July to September), and by medium to deep alluvial soils with textures varying from sandy to silty clay. The districts surveyed in the state of Haryana lie on the alluvial plains of the Yamuna River with some pediments of origin in the Aravalli hills. Climatic conditions are similar to those found in the Punjab, with a mean minimum temperature of 18 °C and maximum of 34 °C, and an average rainfall of 535mm (80% of which is received during the monsoon season, usually from July to September).

The field survey covered four districts in Punjab (Kapurthala, Fatehgarh Sahib, Ludhiana, and Patiala) and three districts in Haryana (Ambala, Karnal and Kurukshetra). These districts were selected purposively to represent intensive rice-wheat cropping systems in these states. These states have extreme specialization of rice and wheat grown in a rotational cropping system. About 60–80% of the gross cropped area of each state has been dedicated to rice and wheat rotations (Singh et al., 2017; DESA, 2020). Within each district, farmers were selected randomly. This resulted in 2,265 farmers surveyed in Punjab (580 in Ludhiana, 546 in Patiala, 570 in Kapurthala, and 569 in Fatehgarh Sahib) and 1,842 farmers in Haryana (652 in Ambala, 571 in Karnal, and 619 in Kurukshetra). The fields to which surveys corresponded were geo-referenced and farmers were requested detailed self-reported information for the largest rice field of the farm on rice yield, varietal information, crop duration, and crop management practices (Table 1). Socio-economic information of farming households such as household size and farm size were also collected. Interviews were conducted right after rice harvest (October–December 2020) by trained enumerators using a semi-structured questionnaire designed for the Android-based ODK (Open Data Kit) platform (https://getodk.org/).

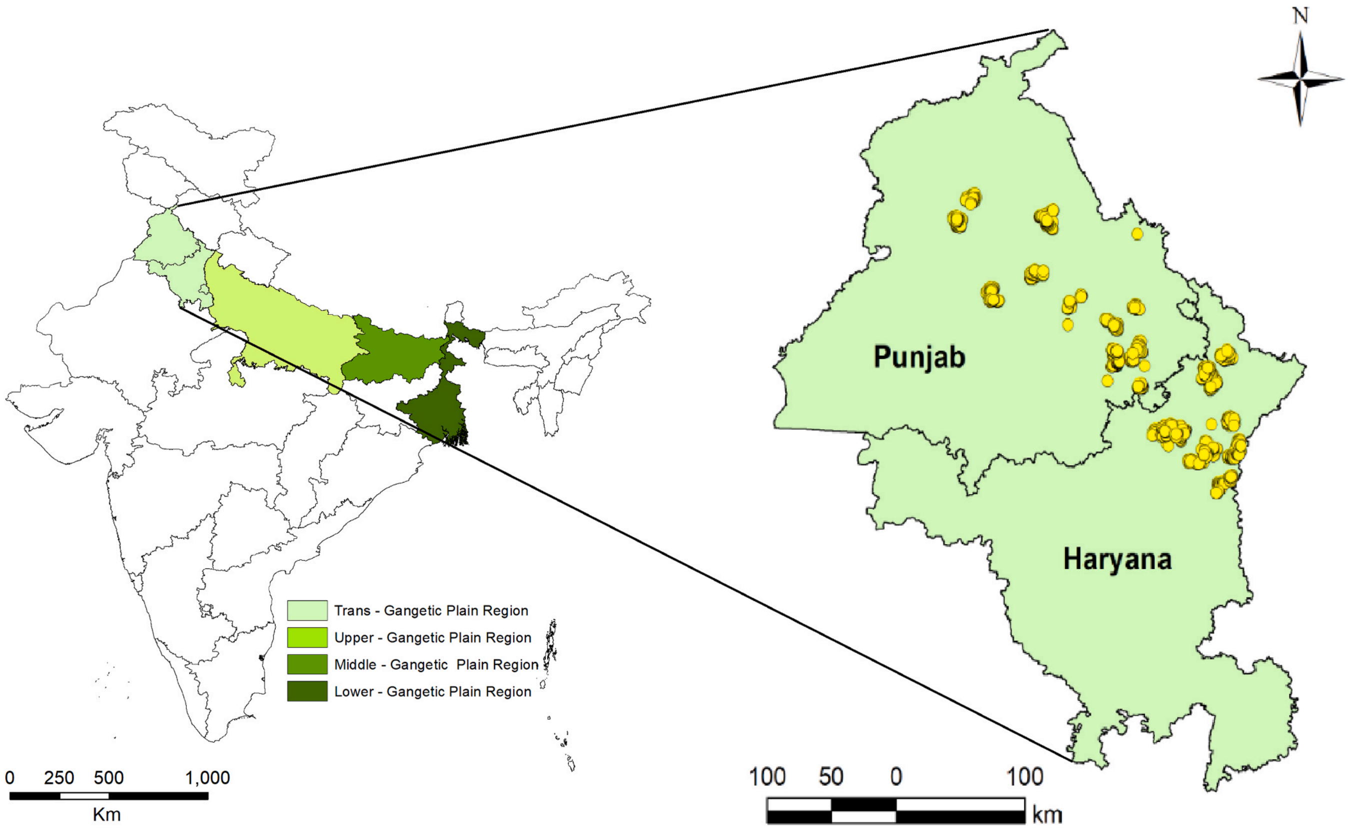

Fig. 1. Location of the surveyed rice fields in the states of Haryana (n = 1842 fields) and Punjab (n = 2265 fields) located in the Northwestern Indo-Gangetic Plains of India during the 2020 *kharif* season.

Table 1
Descriptive statistics of non-basmati rice production systems in Punjab and Haryana during the *kharif* growing season of 2020.

	Average			Standard deviation			Maximum			Minimum		
	LD	MD	SD	LD	MD	SD	LD	MD	SD	LD	MD	SD
Rice grain yield (t ha^{-1})	7.8	7.0	6.9	0.6	0.6	0.6	9.0	8.8	8.1	6.2	4.5	5.0
Tillage operations (*n*)	6.5	5.9	6.1	1.4	1.4	1.4	10.0	12.0	11.0	1.0	1.0	3.0
Sowing date (Julian days)	134.0	141.1	142.9	4.8	7.1	7.5	170.0	182.0	182.0	124.0	122.0	126.0
Harvest date (Julian days)	299.2	287.2	274.7	5.8	7.3	6.6	315.0	318.0	306.0	267.0	253.0	253.0
Growing season (days)	165.2	146.2	131.8	7.8	8.7	4.7	175.0	155.0	135.0	120.0	104.0	104.0
Nursery duration (days)	31.3	28.9	28.7	5.7	5.0	4.3	40.0	40.0	40.0	0.1	0.1	0.1
Number of irrigations (*n*)	47.0	34.8	36.4	8.2	13.8	12.8	60.0	60.0	60.0	30.0	5.0	4.0
N applied (kg ha^{-1})	156.2	159.3	162.1	18.5	21.3	21.1	229.5	229.5	229.5	103.5	80.5	80.5
P_2O_5 applied (kg ha^{-1})	8.9	26.7	31.8	18.4	27.4	27.6	57.5	88.8	97.8	0.1	0.1	0.1
Fungicide applied (kg ai kg ai^{-1})	1.2	1.1	1.1	0.6	0.6	0.7	3.1	3.5	3.9	0.1	0.1	0.1
Herbicide applied (kg ai kg ai^{-1})	1.0	1.0	0.9	0.4	0.5	0.5	2.8	7.5	6.0	0.1	0.1	0.1
Insecticide applied (kg ai kg ai^{-1})	2.2	1.6	1.8	1.1	1.0	1.2	7.4	6.9	8.5	0.1	0.1	0.1
1st top dress of urea (DAT)	10.0	10.2	9.5	2.7	3.3	2.8	20.0	35.0	20.0	6.0	4.0	5.0
2nd top dress of urea (DAT)	21.2	20.6	20.0	3.4	4.4	3.9	30.0	45.0	40.0	13.0	12.0	12.0

Data are disaggregated per variety type. Codes: LD = long-duration variety, MD = medium-duration variety, SD = short-duration variety, DAT = days after transplanting. We observed negligible application of organic inputs to rice, as organic materials are usually applied to higher-value crops such as vegetables, or to market and home gardens. Similarly, K and micronutrient application was negligible and therefore excluded.

2.1.2. *Actual yield (Ya) estimation*

Actual farm yields (Ya) were estimated based on farmer's self-reported yields and measured crop-cut yields (Ycc) taken from a sub-sample of ca. 25% of the surveyed fields (1,014 out of 4,107 fields). The crop-cut yield assessment was done by manually harvesting a 2×2 m^2 quadrant (leaving a minimum of a 5–10 m border from each side of the field) followed by sun drying of bundles of harvested paddy (straw and grain) until constant weight and determining paddy yield at 14% moisture content. Grain moisture content was estimated *in-situ* using a hand-held moisture meter at the time of yield assessment. Farmers were also asked to provide their estimate of rice yield from the crop cut field and for the total area of the field. Rice yields (Y_{self}) were then estimated in t ha^{-1} based on self-reported production and measured field area size, assuming self-reported production was reported at 14% moisture content. The GPS coordinates of the fields where the crop-cut assessment was not done were recorded using the ODK platform by revisiting the field after the interview. Ya of the fields in which crop cuts were not done were obtained from Y_{self} by applying a linear regression fitted between Y_{cc} and Y_{self} ($Y_{cc} = 0.90 + 0.48 \times Y_{self}$; $R^2 = 0.83$; Fig. 2). Fields with a difference between Y_{cc} and Y_{self} greater than 1 t ha^{-1} were removed from the dataset prior to fitting the linear regression (these comprised < 5% of the total sample). Such large discrepancy between

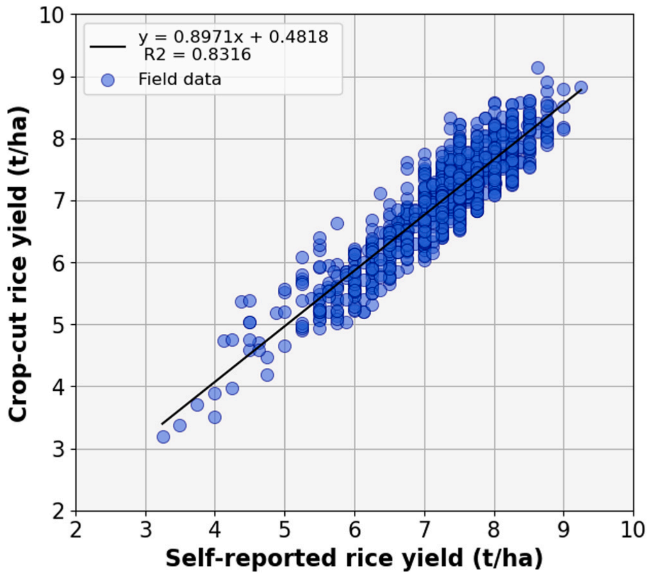

Fig. 2. Relationship between crop cut yield (t ha^{-1}) and self-reported yield (t ha^{-1}) for rice in the Northwestern Indo-Gangetic Plains of India during the 2020 *kharif* season. The solid line shows the linear regression fitted to the data, which was then used to estimate the actual yield for the fields where crop cuts were not conducted.

crop cut and self-reported yields was probably the result of moisture contents below or above 14% while reporting Y_{self}, and/or due to errors in the self-reported production or area of the surveyed field.

2.1.3. Cleaning and curation of data

A web-based dashboard was developed to visualize the data as they were collected from farmers' fields in real-time. The dashboard extracted the relevant data from a server housing the ODK data managed by the Cereal Systems Initiative for South Asia (CSISA) project, with errors/extreme observations identified by employing univariate statistical methods (e.g., boxplots) as dashboard outputs that could be visually assessed. Enumerators were then asked to revalidate any outlying observations by re-interviewing the farmer surveyed. The most common errors during data collection were related to spelling, the number of digits applied to numerical inputs, and due to misinterpretation of units, which were corrected following re-survey of farmers and using expert knowledge.

Univariate outlier screening was conducted with the analysis of the Inter Quartile Range (IQR; boxplot technique) using the name of the rice variety as a sub-category and rice yield, fertilizer inputs, duration of the growing season, and irrigation number as dependent variables. There were many different varieties reported by farmers, all with varying frequency. Varieties reported by farmers were therefore grouped based on their growing season duration (short-, medium- and long-duration varieties). This grouping facilitates the comparison within the groups as short-, medium- and long-duration varieties are assumed to be homogenous among themselves. The first quartile minus 1.5 × IQR was considered as the lower threshold and the third quartile plus 1.5 × IQR was considered as the upper threshold for the dependent variables. The minimum and maximum values for each variable were fixed based on a combination of expert knowledge and the distribution of the data observed for each variable (Table 1). Values of a particular variable greater than the maximum value or lower than the minimum value were identified as outliers and excluded from further analysis. Furthermore, bivariate and multivariate outliers were identified by applying the Robust Mahalanobis Distance (RMD, Gnanadesikan and Kettenring, 1972) method. As an example, an N application rate of 80 kg N ha^{-1} is not a univariate outlier but obtaining a rice yield of 8.0 t ha^{-1} with 80 kg N ha^{-1} is an outlier in the Punjab and Haryana states. RMD is not sensitive to the presence of outliers up to a breakdown point of 50% (i.e., the method generates robust results even if 50% of the data are outliers). The algorithm finds the centre and the scale of the ellipse that represents the cloud of datapoints in the direction of maximum spread by taking a subset of the data, thus identifying potential outliers. If the calculated RMD for a given observation was greater than the cut-off value equal to the 0.975 quantile of the Chi-square distribution at *n* degrees of freedom (i.e., number of variables), then such observation was identified as a potential outlier. The RMD was calculated only when the presence of outliers was expected from the visual observation of the distribution of the data. Datapoints with such outliers were excluded from further analysis. This resulted in 4,107 out of 4,267 samples that were retained for final analysis.

2.2. Secondary data sources

Weather and soil data were obtained from secondary data sources using the GPS coordinates of the surveyed fields to co-locate crop management and yield data with secondary environmental data (Fig. 1). Minimum and maximum temperatures were obtained from the ERA5 hourly re-analysed database (Sabater, 2019), which were converted to daily values by averaging hourly data. Rainfall data at 0.05° × 0.05° resolution were obtained from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS; Funk et al., 2015). CHIRPS is a quasi-global rainfall dataset which combines data from real-time automatic weather stations with infrared data derived from sattellite observations to estimate precipitation. Minimum and maximum temperatures and precipitation data were further averaged over the growing season (i.e., for the dates between sowing and harvesting) and combined with farmers' reported management data obtained from the field survey. Soil texture data (i.e., percentage of sand, silt, and clay in the top 0–30 cm layer) were obtained for each field from the International Soil Reference and Information Centre (ISRIC) soil database at a spatial resolution of 250 m (Hengl et al., 2017). Soil texture data were then used to derive soil classes for each of the observed fields (i.e., fine and medium textured soil) using the USDA textural triangle classification.

2.3. Yield gap analysis

Rice yield gaps in the Northwestern IGP of India were decomposed into efficiency, resource, and technology yield gaps. 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) and actual yields (Silva et al., 2017), and can be explained by sub-optimal crop management in relation to time, space and form of the inputs applied. Technical efficient yields and efficiency yield gaps were estimated for each rice field using stochastic frontier analysis, and were informed by concepts of production ecology (van Ittersum and Rabbinge, 1997). The resource yield gap refers to the difference between highest-farmers' yields (Y_{HF}, i.e., mean Ya above the 90th percentile Ya) and Y_{TEx}, and can be attributed to sub-optimal amounts of inputs applied. Lastly, 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 (Silva et al., 2017a, 2017b). The reader is referred to (Silva et al., 2017a) for a visual illustration of these concepts.

The yield gap analysis focused on non-*basmati* rice only due to the small sample for *basmati* rice (scented rice) and differential management (e.g., N management and variety types) requirement of *basmati* compared to non-*basmati* rice. The area under non-*basmati* rice was 2.3 M ha out of 2.9 M ha of rice area in Punjab and 0.6 M ha out of 1.3 M ha of rice area in Haryana (Udhayakumar et al., 2021). The area share of *basmati* rice area in both states varies between 20% and 50% of the total rice area depending on the year (APEDA, 2018).

2.3.1. Y_{TEx} and efficiency yield gaps

Stochastic frontier analysis (Kumbhakar and Lovell, 2000) is useful to estimate the maximum yield that could have been produced in farmers' fields with the level of inputs used. Stochastic frontiers differentiate two random errors – technical inefficiency u_i (translated to agronomic terms as the efficiency yield gap) and random noise, or v_i, hence separating the effects of sub-optimal crop management from random noise in the response variable. The relationship between rice yields on the one hand, and biophysical conditions and inputs applied on the other, was assumed to follow a translog functional form, which generic formulation is as follows (Eq. 1):

$$ln \quad y_i = \quad \beta_0 + \sum_{k=1}^{K} \beta_k lnx_{ki} + \frac{1}{2}\sum_{k=1}^{K}\sum_{j=1}^{K}\theta_{kj}(\ln x_{ki}) \times (lnx_{ji}) + v_i - u_i \tag{1}$$

$$\text{Eff. Yg}_i = 1 - \exp(-ui) \tag{2}$$

$$Y_{TExi} = Ya_i/\exp(-ui) \tag{3}$$

where y_i is the rice grain yield of the i^{th} farmer, x_{ki} is the k^{th} input (fertilizer, irrigation, variety, etc.) used by the i^{th} farmer, β_k is an unknown vector of parameters to be estimated, and θ_{kj} are the parameters describing the second-order effects (squared and interactions) on the response variable. 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 parameter $\gamma = \sigma_u^2/(\sigma_u^2+\sigma_v^2)$ represents the fraction of the model residuals explained by the random error u_i, from which the efficiency yield gap is calculated (Eq. 2). Stochastic frontier models with a Cobb-Douglas functional form (i.e., considering first-order variables only) were also fitted to the data for comparative purposes. Log-likelihood ratio tests comparing nested Cobb-Douglas and translog stochastic frontier models indicated the stochastic frontier model with a translog functional form fitted the data best (i.e., the log-likelihood value of the translog model was significantly greater than that of the Cobb-Douglas model at $p < 0.0001$). Efficiency yield gaps (Eq. 2) and Y_{TEx} (Eq. 3) were thus estimated from the stochastic frontier model with the translog functional form.

The vector of biophysical and management variables, x_{ki}, was defined according to concepts of production ecology (van Ittersum and Rabbinge, 1997). The variables maximum and minimum temperature (°C), sowing date, seed rate (kg ha^{-1}) and rice variety (short-, medium-, and long-duration) were included in the analysis to capture the effects of growth-defining factors on crop yield. Growth-limiting factors in relation to water and nutrient management were captured in the analysis with the following variables: precipitation (mm), number of irrigations (*n*), soil type (fine and medium textured soils), number of tillage operations (*n*), N applied (kg N ha^{-1}) and P applied (kg P_2O_5 ha^{-1}). The extent to which growth-reducing factors affected crop yields was assessed through the variables including the total amount of fungicide, herbicide, and insecticide applied, seed treatment (yes/no) and weed control method (manual, herbicide, or both). The amount of herbicides applied per hectare were divided by the recommended dose to standardize the effect of high and low dose of herbicides. A similar transformation was done to the amount of fungicides and insecticides applied. Multicollinearity between the aforementioned variables was checked using the Variable Inflation Factor (VIF) as implemented in the *vif*() function of the *car* package in R (Fox and Weisberg, 2019). All variables used in the analysis had a VIF value below 5 and hence, were not multicollinear. All continuous variables were mean-scaled and log-transformed prior to the analysis so that model parameters can be interpreted as elasticities, assuming all other inputs kept at their mean level.

The stochastic frontier model described in Eq. (1) was also estimated with inefficiency effects to identify the deteminants of crop management on the efficiency yield gap (Battese and Coelli, 1995). To do so, the production frontier and the inefficiency effects were estimated simultaneously in a single step in which the production frontier was defined as per Eq. (1) and the inefficiency effects were described as follows (Eq. 4):

$$u_i = \sum\nolimits_j^J \delta_j z_{ji} + \varepsilon_i \tag{4}$$

where the z_i comprises the sources of inefficiency due to sub-optimal crop management and ε is a random error. In this model, u_i is assumed to be i.i.d. following a $N^+(\sum_j^J \delta_j z_{ji}, \sigma_u^2)$ distribution (Battese and Coelli, 1995). The vector z_i includes the duration of the nursery of the rice seedlings (days), the duration of the fallow period (days), the days of the first and second top-dress application of urea (days after transplanting, DAT), the number of insecticide splits (*n*) applied and the days of the first application of fungicide, herbicide, and insecticide (DAT). The stochastic frontier models were fitted to the pooled data using the *sfa*() function of the R package *frontier* (Coelli and Henningsen, 2020).

2.3.2. Y_{HF} and resource yield gaps

Farmers' fields were categorized into highest-, average- and lowest-yielding based on the distribution of Ya observed in the dataset. Field categories were defined for unique variety × soil type combinations to ensure yield differences between fields in each category were due to variation in crop management rather than to differences in genotype and biophysical factors. Rice varieties reported by farmers were further classified into three groups based on growth duration (i.e., short, medium, and long) using expert knowledge from agronomists in the region. Soil types with fine and medium texture were retrieved from ISRIC database using the field-specific GPS coordinates. Climatic conditions were assumed to be homogenous across Punjab and Haryana, as the IGP are characterized by flat alluvial soils (see Section 2.1.1).

Highest-yielding fields were defined as those with rice yields above the 90^{th} percentile of Ya, and highest-farmers' yields (Y_{HF}) were calculated as the mean Ya in the highest-yielding fields. The resource yield gap was estimated for each field as the difference between Y_{HF} and Y_{TEx}. Lowest-yielding fields refer to the fields where rice yields were below the 10^{th} percentile of Ya, and lowest-farmers' yields (Y_{LF}) were calculated as the mean Ya in lowest-yielding fields. Finally, average-yielding fields include the fields where rice yields were between the 10^{th} and 90^{th} percentile of Ya, and the average-farmers' yield (Y_{AF}) were calculated as the mean Ya in average-yielding fields. Quantile regressions were fitted to the 98^{th} percentile of the pooled data with the *smf()* function of the *statsmodels* library in Python (Seabold and Perktold, 2010) to assess the rice yield response to the number of irrigations and N applied. A logistic functional form of the type $y = a + b \times x + c \times 0.99x$ was assumed for this relationship. A similar analysis was conducted for the relationship between sowing and harvest dates on the one hand and rice yield on the other. A linear relationship of the type $y = a \times x + b$ was assumed for the latter.

2.3.3. Yp and technology yield gaps

Yp for irrigated rice in the Northwestern IGP of India were retrieved from the Global Yield Gap Atlas (GYGA, www.yieldgap.org). GYGA includes data on yield ceilings for yield gap analysis simulated with calibrated crop models embedded within a spatial framework (van Ittersum et al., 2013). Yp of irrigated rice in India included in the GYGA was simulated with the APSIM crop model (Holzworth et al., 2014) for the monsoon *kharif* season over the years 1997–2015 (Grassini et al. 2015; van Bussel et al., 2015). Further details about the parametrization of the crop model, the weather data used, and the cropping systems considered in the simulations are available at www.yieldgap.org/India.

The average Yp over the years 1997–2015 for a given climate zone was taken as a benchmark for the rice yields obtained in the field survey conducted during the *kharif* season of 2020. Ideally, the Yp benchmark should coincide with the year of the Ya data, but this was not possible in this study due to lack of updated data in GYGA. Yet, the average Yp values adopted here for irrigated rice in the Northwestern IGP of India can be considered reliable because there is little evidence of major changes in management practices over the past decade and because of the small inter-annual variability of Yp for irrigated rice in the region (CV = 13%; data not shown). The average Yp from the GYGA was then obtained for each field using field-specific GPS coordinates and the technology yield gap was calculated as the difference between Yp and Y_{HF} for unique variety × soil type combinations.

2.4. Sustainability assessment in relation to N-use efficiency

N fertilizers are an important driver of cereal yields, particularly rice, in South Asia (Ladha et al., 2020), but the nitrogen use efficiency (NUE) of South Asian cereal cropping systems remains low (Farnworth et al., 2017). Opportunities exist to further enhance yield, profitability and NUE in these systems through adoption of various precision nutrient management techniques (Sapkota et al., 2017, 2020, 2021). Therefore, a detailed NUE analysis was conducted to assess the scope to reduce N inputs without compromising actual yields. To do so, farmers' fields were classified into four groups of N partial factor productivity (PFP-N, kg grain kg^{-1} N applied), a commonly used indicator of NUE obtainable from farmers' field data that is defined as the ratio between grain yield and N applied (Dobermann, 2005). The four groups were defined based on actual yields and N applied as follows: (1) the high yield and high N applied group (HYHN) includes fields with actual yields above the mean actual yield and with N applied above the mean N applied observed in the database, (2) the high yield and low N applied group (HYLN) includes fields with actual yields above the mean actual yield and with N applied below the mean N applied observed in the database, and (3) the low yield and low N applied group (LYLN) includes fields with actual yields below the mean actual yield and with N applied below the mean N applied observed in the database. Finally, (4) the low yield and high N applied group (LYHN) includes fields with actual yields below the mean actual yield and with N applied above the mean N applied observed. PFP-N is consequently expected to be greater, on average, for the HYLN group followed by the LYLN, HYHN and LYHN groups.

Following the field classification into different PFP-N groups, further analyses looking into variety type, N split, N amount per split and N time were conducted to identify opportunities to reduce N applied with little or no reductions in rice yields, or in other words, to increase PFP-N. For each PFP-N group, the variability in PFP-N was assessed using boxplots and the relative proportion of short-, medium- and long-duration varieties was estimated to understand the interaction between variety type and NUE. The average amount of N applied per split, both in absolute and relative terms (i.e., in relation to total N applied) was also summarized for each PFP-N group to assess whether differences in PFP-N were attributed to the number of N splits, to the amount of N applied per split, or both. Moreover, differences in PFP-N were further assessed for fields with three or four applications of urea and with or without application of diammonium-phosphate (DAP). Finally, the timing of the different N splits was compared for each PFP-N group using N calendars (Silva et al., 2021a). These summarized the number of fields receiving a given N split in each calendar week (Supplementary Fig. S1).

3. Results

3.1. Rice yield gaps in the Northwestern Indo-Gangetic Plains

Rice actual yield (Ya) across the surveyed fields was on average 7.2 t ha^{-1} (Fig. 3A), which corresponds to ca. 73% of Yp (Fig. 3B). The highest-farmers' yields (Y_{HF}) and technical efficient yields (Y_{TEx}) across the pooled sample were, on average, 8.1 and 7.6 t ha^{-1} (Fig. 3A), which corresponds to ca. 82% and 78% of Yp (Fig. 3B), respectively. Differences in Yp, Y_{HF}, Y_{TEx} and Ya were small across states and districts (Fig. 3). For instance, considering the state of Haryana, Ya was greatest in Kurukshetra (7.3 t ha^{-1} or ca. 73% of Yp) and smallest in Ambala (6.4 t ha^{-1} or ca. 67% of Yp), while Ya in Punjab was greatest in Ludhiana (7.7 t ha^{-1} or ca. 84% of Yp) and smallest in Fatehgarh Sahib (6.9 t ha^{-1} or ca. 69% of Yp). In all districts, except Ludhiana where actual yield was slightly above 80% of Yp, narrowing yield gaps to the Y_{HF} resulted in a yield gap closure of ca. 80% of Yp (Fig. 3B).

Rice yield gaps were mostly attributed to the technology yield gap, followed by efficiency and resource yield gaps (Fig. 3). The technology yield gap was on average 1.8 t ha^{-1} (corresponding to ca. 18% of Yp), while the efficiency and resource yield gaps were, on average, 0.5 and 0.4 t ha^{-1} (ca. 5% of Yp), respectively. Yet, there was considerable

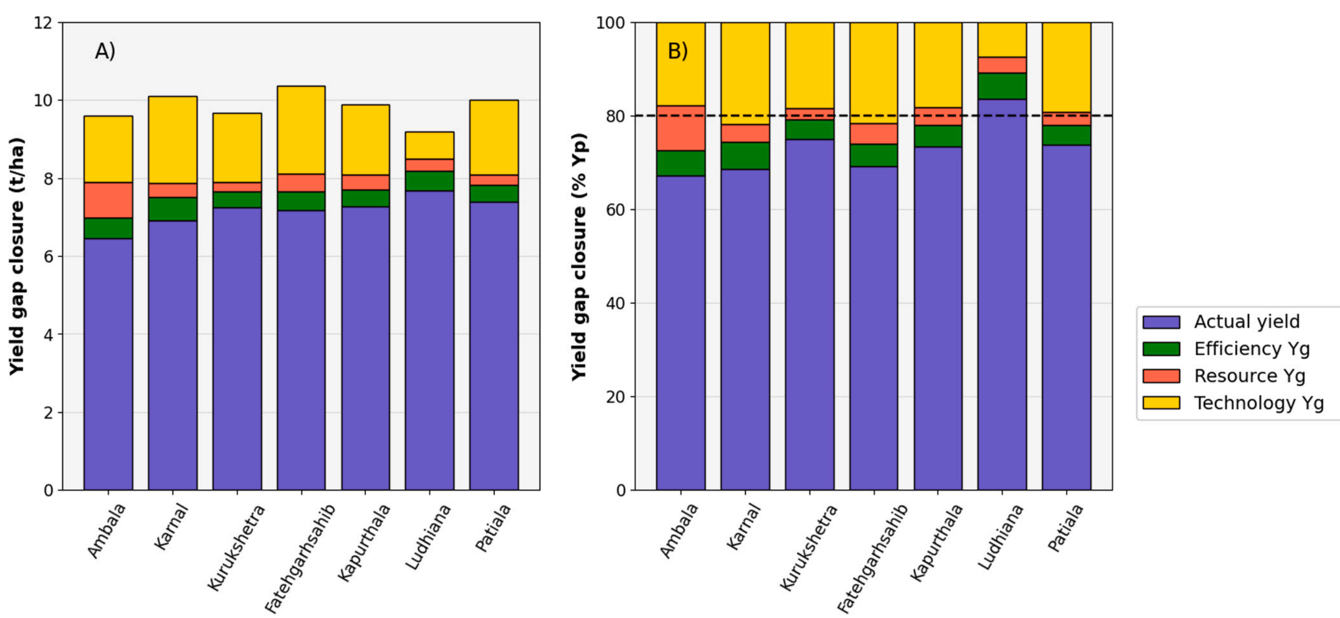

Fig. 3. Rice yield gap decomposition into efficiency, resource and technology yield gaps for the state of Haryana (Ambala, Karnal and Kurukshetra) and Punjab (Fatehgarh Sahib, Kapurthala, Ludhiana and Patiala) in the Northwestern Indo-Gangetic Plains of India during the 2020 *kharif* season. Panel (A) and (B) shows 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).

variation in efficiency and resource yield gaps across the surveyed fields (Fig. 4). The efficiency yield gap exhibited a normal distribution with values ranging between nil and ca. 1.6 t ha^{-1} (Fig. 4A). No major differences in the mean and distribution of the efficiency yield gap were observed between fields with varieties of different growth duration (Fig. 4A). The distribution of the resource yield gap was slightly left skewed and smaller for fields with short-duration varieties than with medium- or long-duration varieties (Fig. 4B). Overall, greater Ya resulted in smaller efficiency (Fig. 4C) and resource yield gaps (Fig. 4D) independently of the varieties cultivated, which indicates that Ya values close to Yp were observed in some of the fields surveyed (8.0–9.0 t ha^{-1} vs. 8.7–10.5 t ha^{-1}).

3.2. Production frontier and drivers of Ya variability

The gamma value of the fitted stochastic frontier models was 0.82 (Table 2), meaning that the random errors u_i contribute more to the overall model residuals than the random errors v_i, and hence, that a stochastic frontier approach was preferred over a multiple regression approach based on Ordinary-Least Squares (OLS).

The sign, magnitude and significance level of the parameter estimates was rather similar across the different stochastic frontier models fitted (Table 2). As Model 3 described the variability observed in the data better than the other models, this model was chosen for describing the results. Soil texture had a small but statistically significant effect on rice yields, with the latter being 0.5% greater in soil types with medium texture than in soil types with fine texture. Similarly, seed treatment had a small but statistically significant positive effect on rice yield: treated seeds resulted in 1.6% greater yields than untreated seeds. Rice yields were also statistically different across varieties with different growth duration, with short- and medium-duration varieties yielding 4–5% less than long-duration varieties. There was no statistically significant yield difference between fields in which both herbicides and hand-weeding were used and fields where only herbicides were used. Yet, rice yields were significantly greater (ca. 5%) in fields where herbicides were used than in fields reporting only hand-weeding or no weeding.

There was a statistically significant positive effect of maximum temperature on rice yields, with a 1% change in maximum temperature resulting in ca. 0.39% increase in rice yields. By contrast, minimum temperature and precipitation had a statistically significant negative effect on rice yields: a 1% change in minimum temperature and precipitation resulted in ca. 0.14% and 0.10% decreases in rice yields, respectively. The effects of temperature and precipitation on rice yield were consistent across the four stochastic frontier models fitted (Table 2), although the exact effect size was slightly different for each model. For sowing date, both the quadratic and linear terms were statistically significant, indicating rice yields decreased until a minimum level was reached, after which rice yields increased. Yet, the effect of

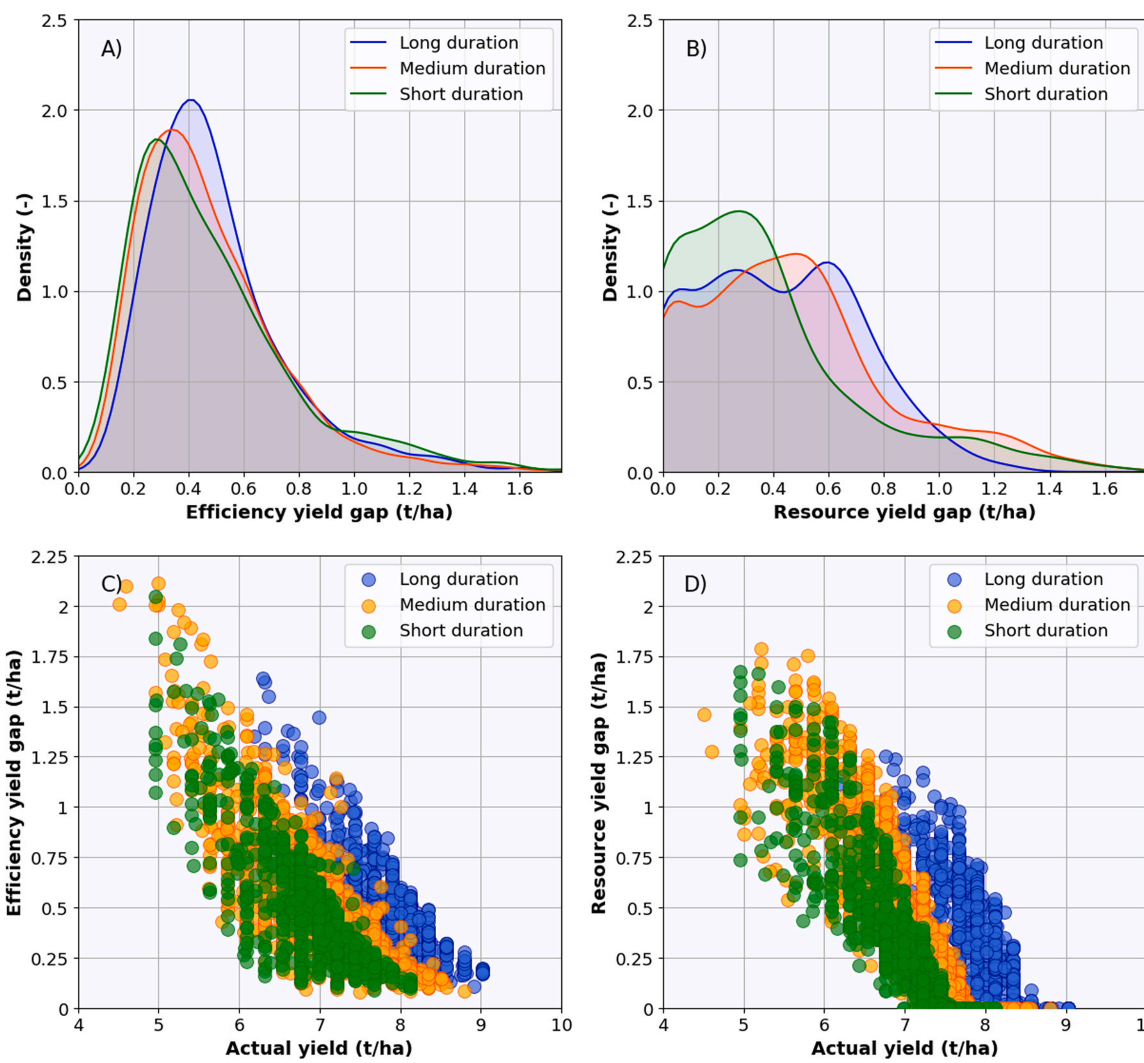

Fig. 4. Density plot of the (A) efficiency yield gap and (B) resource yield gap as faceted by variety type. Scatterplots showing the relationship between the efficiency yield gap and the resource yield gap on the one hand, and the actual yield on the other are shown in panels (C) and (D), respectively.

Table 2
Parameter estimates of the stochastic frontier models describing non-basmati rice production systems in the Northwestern Indo-Gangetic Plains of India during the *kharif* growing season of 2020.

Variables	CD without inefficiency effects (Model 1)	CD with inefficiency effects (Model 2)	TL without inefficiency effects (Model 3)	TL with inefficiency effects (Model 4)
Production frontier				
Intercept	0.091***	0.093***	0.072***	0.075***
Texture (Medium)	0.005*	0.005*	0.005*	0.005*
N applied (kg N ha^{-1})	0.005	-0.005	-0.001	0.001
N applied^2			-0.286***	-0.272**
P_2O_5 applied (kg P_2O_5 ha^{-1})	-0.002***	-0.001 #	-0.003	-0.002
P_2O_5 applied^2			0.001	0.001
Irrigation number (*n*)	0.028***	0.030***	-0.026	-0.018
Irrigation number^2			0.006	0.009
Sowing date (DOY)	-0.017	-0.036	-0.307***	-0.299***
Sowing date^2			1.555**	1.588**
Tillage number (*n*)	-0.013**	-0.010*	-0.022**	-0.018*
Tillage number^2			0.047*	0.052**
Fungicide applied (kg ai kg^{-1} ai)	-0.005***	0.004*	0.013***	0.012***
Fungicide applied^2			0.022***	0.011***
Herbicide applied (kg ai kg^{-1} ai)	-0.003	0.001	0.001	0.003
Herbicide applied^2			0.014*	0.013*
Insecticide applied (kg ai kg^{-1} ai)	0.006***	0.006**	0.001	0.009*
Insecticide applied^2			0.001	0.013***
Seed rate (kg ha^{-1})	-0.004	-0.004	0.001	-0.001
Seed rate^2			-0.089**	-0.080*
Variety type (MD)	-0.049***	-0.050***	-0.038***	-0.038***
Variety type (SD)	-0.058***	-0.058***	-0.046***	-0.045***
Seed treatment (Yes)	0.020***	0.018***	0.017***	0.014***
Weed control (Herbicide and manual)	-0.005 #	-0.002	-0.003	0.001
Weed control (Manual)	-0.024**	-0.026**	-0.062**	-0.066***
Weed control (None)	-0.024*	-0.024*	-0.055**	-0.055**
Precipitation (mm)	-0.092***	-0.098***	-0.102***	-0.103***
Maximum temperature (∘C)	0.404***	0.278***	0.385***	0.343***
Minimum temperature (∘C)	-0.137***	-0.140***	-0.143***	-0.146***
N × P_2O_5			0.005	0.006
N × Irrigation number			0.055**	0.051**
N × Sowing date			-0.176	-0.283 #
N × Tillage number			0.055	0.058
N × Fungicide			0.016	0.012
N × Herbicide			-0.043**	-0.040**
N × Insecticide			0.003	-0.001
N × Seed rate			0.033	0.077*
P_2O_5 × Irrigation number			-0.005***	-0.005***
P_2O_5 × Sowing date			-0.004	-0.003
P_2O_5 × Tillage number			-0.001	-0.002
P_2O_5 × Fungicide			0.000	0.000
P_2O_5 × Herbicide			-0.001	-0.001
P_2O_5 × Insecticide			0.001	0.001
P_2O_5 × Seed			-0.004 #	-0.004 #
Irrigation number × Sowing date			0.091*	0.071
Irrigation number × Tillage number			0.005	0.005
Irrigation number × Fungicide			-0.015***	-0.013***
Irrigation number × Herbicide			0.000	0.000
Irrigation number × Insecticide			-0.003	-0.003
Irrigation number × Seed			-0.079***	-0.078***
Sowing date × Tillage number			-0.333***	-0.334***
Sowing date × Fungicide			-0.066 #	-0.050
Sowing date × Herbicide			-0.040	-0.040
Sowing date × Insecticide			0.040	0.045
Sowing date × Seed			-0.283**	-0.244*
Tillage number × Fungicide			-0.014*	-0.012*
Tillage number × Herbicide			-0.003	-0.001
Tillage number × Insecticide			-0.012 #	-0.013 #
Tillage number × Seed			-0.001	-0.009
Fungicide × Herbicide			-0.002	-0.001
Fungicide × Insecticide			-0.002	-0.004 #
Fungicide × Seed			-0.001	0.000
Herbicide × Insecticide			0.002	0.003
Herbicide × Seed			0.008	0.008
Insecticide × Seed			0.003	-0.001
N × medium duration variety			0.035	0.037
N × short duration variety			0.004	-0.003
Irrigation number × MD variety			0.021	0.018
Irrigation number × SD variety			0.019	0.017
Sowing date × MD variety			0.248**	0.223**
Sowing date × SD variety			0.163 #	0.154 #
Seed × MD variety			-0.042***	-0.045***
Seed × SD variety			-0.013	-0.015

(*continued on next page*)

Table 2 (*continued*)

Variables	CD without inefficiency effects (Model 1)	CD with inefficiency effects (Model 2)	TL without inefficiency effects (Model 3)	TL with inefficiency effects (Model 4)
Inefficiency effects				
Nursery duration (days)		-0.002		0.001
Urea 1st top dress (DAT)		-0.009		-0.032*
Urea 2nd top dress (DAT)		0.153***		0.165***
Fallow duration (days)		0.009		0.005
Insecticide splits (#)		0.020**		0.021**
1st insecticide application (DAT)		-0.016***		-0.026***
1st fungicide application (DAT)		0.037***		0.025***
1st herbicide application (DAT)		0.017***		0.013***
Model evaluation				
SigmaSq (σ^2)	0.010***	0.010***	0.009***	0.009***
Gamma (γ)	0.812***	0.817***	0.816***	0.820***
Mean technical efficiency (%)	0.94	0.94	0.94	0.94
Sample size (n)	4107	4107	4107	4107

Codes: CD = Cobb-Douglas; TL = Translog; LD = long-duration variety, MD = medium-duration variety, SD = short-duration variety, DAT = days after transplanting. Significance codes: '***' 0.1%, '**' 1%, '*' 5% and '#' 10%. Note: Supersript ^{2} indicates the square of the variable.

sowing date on rice yield was also generally small and variety-specific as indicated by the statistically significant positive interaction between sowing date and medium-duration varieties. Nonetheless, statistically significant effects of sowing date on rice yield were only observed in Models 3 and 4, but not in Models 1 and 2, neither of which consider second-order terms. The first-order or second-order terms of irrigation number were not statistically significant in Models 3 and 4, as opposed to a statistically significant positive effect of irrigation number on rice yield in Models 1 and 2. Finally, the effect of seed rates on rice yields was not statistically significant for the first order term in either model. It was conversely significant and negative for the squared term in Models 3 and 4. Increasing seed rates was associated with decreased rice yield responses to irrigation number, sowing date and to medium-maturity varieties compared to long-duration varieties, but again the effects were small and may not be agronomically relevant.

The effects of N and P applied on rice yield were mostly non-significant across the fitted models, a characteristic of high-yielding cropping systems (Silva et al., 2017b), whereas the squared and linear effects of tillage number and fungicide active ingredient on rice yield were statistically significant but with a small effect sizes (Table 2). In the case of N applied, only the squared term was statistically significant. Rice yield response to N applied increased with increases in the number of irrigations and decreased with increases in herbicide use. The number of tillage operations reduced rice yields slightly, until a minimum level was reached. Rice yield response to sowing date was negatively affected by the number of tillage operations, suggesting that if sowing is delayed then farmers may wish to consider reducing the tillage rate to avoid yield penalty. Fungicide active ingredient positively affected rice yields, but less so with increasing number of irrigations applied and tillage operations.

The analysis of the inefficiency effects revealed that sub-optimal management in relation to the timing of the inputs applied explained part of the variation observed in the efficiency yield gap (Table 2). For instance, late applications of the first fertilizer top-dress, and early applications of the second fertilizer top-dress resulted in smaller efficiency yield gaps. Similarly, earlier application of insecticide and later application of fungicide and herbicide also contributed to a smaller efficiency yield gap.

3.3. Crop management in highest-, average-, and lowest-yielding fields

Rice yields were on average 8.0, 7.1 and 5.9 t ha^{-1} in highest-, average- and lowest-yielding fields, respectively (Fig. 5; Table S1). The number of irrigations was smaller in lowest-yielding fields (26 irrigations) than in average- and highest-yielding fields (38 and 42 irrigations, respectively; Fig. 5A). Rice yield response to irrigation number for the 98th percentile followed a non-linear relationship with diminishing returns (intercept of ca. 2 t ha^{-1} and a local maximum of 8.6 t ha^{-1}, which was reached with 45 irrigations) for the fields reporting more than 20 irrigations during the growing season (Fig. 5A). No relationship between rice yield and irrigation number was observed for fields reporting less than 20 irrigations (Fig. 5A) because these fields were in areas with low hydraulic conductivity (i.e., Ambala district; data not shown). Despite the yield difference between highest-, average-, and lowest-yielding fields, there was no difference in the amount of N applied in each field category (Fig. 5B). On average 159 kg N ha^{-1} was applied in highest-, average-, and lowest-yielding fields (Fig. 5B and Table S1). Similar to irrigation number, rice yield response to N applied for the 98th percentile followed a non-linear relationship with diminishing returns (Fig. 5B). The intercept was predicted at ca. 1.5 t ha^{-1} and a local maximum at 8.5 t ha^{-1} with ca. 150 kg N ha^{-1} applied, beyond which rice yield slightly declined (Fig. 5B).

Rice yield declined with later sowing date (Fig. 5C) and increased with later harvest date at the 98th percentile (Fig. 5D). Rice yield declined by 20 kg day^{-1} after the sowing date of May 1st (day of the year, DOY, 122) and increased by 30 kg day^{-1} after a harvest date of September 9th (DOY 253). Sowing and harvest dates were dependent on the type of rice varieties cultivated (Fig. 5C and 5D). Long-duration varieties were sown earlier (May 14, on average) and harvested later (October 26, on average), than medium- and short-duration varieties. Medium-duration varieties were sown on average on May 21 and harvested on October 14, whereas short-duration varieties were sown on average on May 22 and harvested on October 1. No major differences in other crop management practices were observed between highest-, average- and lowest-yielding fields, respectively (Table S1).

3.4. N management and N-use efficiency assessment

Out of 4,107 fields surveyed in Punjab and Haryana, 18%, 35%, 21% and 26% were classified as HYHN, HYLN, LYHN and LYLN, respectively. Average N applied in HYHN, HYLN, LYHN and LYLN groups was ca. 180, 150, 180 and 145 kg N ha^{-1}, corresponding to an average rice yield of 7.5, 7.7, 6.6 and 6.5 t ha^{-1}, respectively (Table 3). Clearly, N applied was rather similar across the different PFP-N groups, yet there were considerable differences in rice yield across groups (Fig. 6A, Table 3). PFP-N for the LYLN group was on average 47 kg grain kg^{-1} N, which was 20% greater than the average PFP-N of the LYHN group (37 kg grain kg^{-1} N; Fig. 6A). Conversely, PFP-N for the HYLN group was on average 52 kg grain kg^{-1} N; this was also 20% greater than the PFP-N of 41 kg grain kg^{-1} N observed in the HYHN group (Fig. 6A).

Fields with long-duration varieties were mostly found in the HYLN group (Fig. 6B). The proportion of fields with medium- and short-duration varieties was similar across the different PFP-N groups, with 30% in the LYHN and LYLN groups and 20% in the HYLN and HYHN

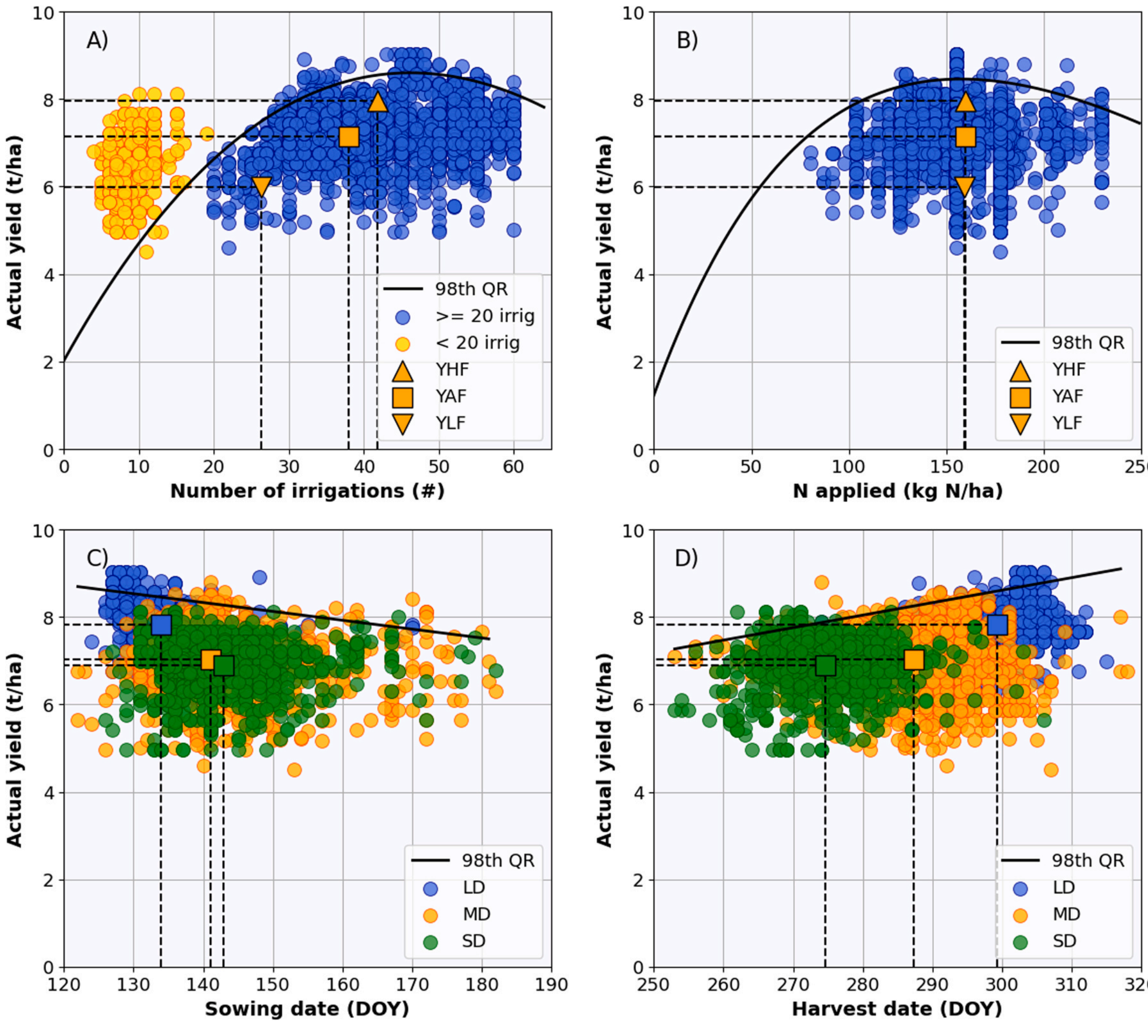

Fig. 5. Rice yield response to (A) number of irrigations, (B) N applied, (C) sowing date and (D) harvest date in the Northwestern Indo-Gangetic Plains of India during the 2020 *kharif* season. Solid lines show the 98th quantile regressions. Dashed lines in (A) and (B) show the average rice yield on the one hand and the average irrigation number and N applied on the other, respectively, for highest- (Y_{HF}), average- (Y_{AF}) and lowest-yielding fields (Y_{LF}). Dashed lines in (C) and (D) show the average rice yield on the one hand and the average transplanting and harvest dates on the other, respectively, for long- (LD), medium- (MD) and short-duration varieties (SD). Fields with irrigation number lower than 20 were located in a region with low hydraulic conductivity and hence, are shown separately in panel (A).

groups (Fig. 6B). PFP-N was 53.5 kg grain kg^{-1} N for long-duration varieties in the HYLN group and greater than 50 kg grain kg^{-1} N for medium- and short-duration varieties in the HYLN group (data not shown). PFP-N was also similar across the different variety types for the fields classified as LYLN (47 kg grain N kg^{-1} N), LYHN (37 kg grain kg^{-1} N) and HYHN groups (41 kg grain kg^{-1} N, data not shown).

An average of 50 kg N ha^{-1} was applied during 1st and 2nd urea splits, irrespective of the PFP-N group (Fig. 6C). N applied in the 1st and 2nd urea splits was ca. 60% of the total N applied in LYHN and HYHN groups and 70% of the total N applied in LYLN and HYLN groups (Fig. 6D). N applied on the 3rd split was also on average ca. 50 kg N ha^{-1} for the LYHN and HYHN groups, but slightly lower for the LYLN and HYLN groups, ca. 38 and 45 kg N ha^{-1}, respectively (Fig. 6C). The latter corresponded to 30% of total N applied for LYHN, HYHN and HYLN groups and to 25% of total N applied for the LYLN group (Fig. 6D). A 4th urea split was only observed for fields classified as LYLN and HYHN groups, with an average N applied of 5 kg N ha^{-1} (Fig. 6C), or 3% of total N applied (Fig. 6D), whereas less than 1% of the fields the high PFP-N groups (LYLN and HYLN) reported a 4th urea split. On average 20 kg N ha^{-1}, or 10% of total N applied, was provided as DAP, mostly basal, in the low PFP-N groups (LYHN and HYHN), whereas barely any N was applied as DAP in the high PFP-N groups (LYLN and HYLN; Fig. 6C and 6D). In summary, the greater PFP-N observed in the LYLN and HYLN groups, relative to the LYHN and HYHN groups, was associated with slightly lower amounts of N applied in the 3rd urea split and with barely any N applied as a 4th urea split late in the season and as DAP early in the season.

The variation observed in PFP-N was partly explained by the number of urea splits and by the type of fertilizer used (Fig. 6E–H), and partly by the timing of N application of the different splits (Table 2; Suppl. Fig. S1). The most common N management strategy observed in the low PFP-N groups was the application of three urea splits with the application of basal DAP. The latter was observed on 723 and 579 fields in the LYHN and HYHN groups, respectively (Fig. 6E and 6F). Conversely, most fields in high PFP-N groups used 3 urea splits only (i.e., 771 fields in the LYLN group and 1,307 fields in the HYLN group; Fig. 6G and 6H). For the LYHN group, PFP-N was slightly greater in fields with three urea splits than in fields with four urea splits, 37 vs. 33 kg N kg^{-1} N, independently of whether basal DAP was used or not (Fig. 6E). For the HYHN group, PFP-N was lower on average for the fields receiving four applications of urea and basal DAP, i.e., 36 kg grain kg^{-1} N, than for the fields with three urea applications (with and without basal DAP, 43 kg grain kg^{-1} N, respectively) and with four urea applications without basal DAP (41 kg grain kg^{-1} N; Fig. 6F). Finally, no major differences in PFP-N

Table 3
Sample size and average value of selected management practices across different N partial factor productivity groups.

	HYHN	HYLN	LYHN	LYLN
Number of fields (n)	724	1,447	865	1,071
Sample size per district				
Ambala	45	69	287	251
Kurukshetra	282	81	175	81
Karnal	123	86	190	172
Ludhiana	42	444	33	61
Patiala	20	345	8	173
Kapurthala	210	155	171	34
Fatehgarh Sahib	1	267		301
Rice grain yield (t ha^{-1})	7.5	7.7	6.6	6.6
N applied (kg N ha^{-1})	181.5	149.1	178.8	143.0
PFP (kg grain kg^{-1} N)	41.4	51.8	37.0	47.0
Nitrogen splits (*n*)	4.1	3.1	4.1	3.2
DAP basal (kg ha^{-1})	45.7	40.6	44.3	46.1
DAP 1st top dress (kg ha^{-1})	45.2	46.7	46.1	42.4
DAP 1st top dress (DAT)	7.2	5.6	5.9	6.5
Urea 1st top dress (kg ha^{-1})	45.8	44.3	45.1	44.1
Urea 2nd top dress (kg ha^{-1})	45.2	44.0	45.1	43.1
Urea 3rd top dress (kg ha^{-1})	44.8	40.5	44.4	36.1
Urea 4th top dress (kg ha^{-1})	30.9	18.0	30.1	25.0
Urea 1st top dress (DAT)	10.2	9.3	10.3	10.4
Urea 2nd top dress (DAT)	20.7	19.9	21.2	20.9
Urea 3rd top dress (DAT)	33.1	32.1	33.5	31.7
Urea 4th top dress (DAT)	40.6	38.3	41.3	37.6
Irrigation number (*n*)	43.7	41.0	32.9	31.8
Sowing date (Julian day)	139.2	138.5	141.3	142.3
Harvest date (Julian day)	285.2	291.0	283.2	283.5

Data refer to the non-basmati rice during the *kharif* 2020 growing season. Codes: LD = long-duration variety, MD = medium-duration variety, SD = short-duration variety, DAT = days after transplanting; HYHN = high yield high N; HYLN = high yield low N; LYHN = low yield high N; LYLN: low yield low N.

were observed on average for the LYLN and the HYLN groups across number of urea splits and use of basal DAP with an average PFP-N of ca. 50 kg grain kg^{-1} N (Fig. 6G and 6H).

4. Discussion

4.1. High-yielding rice systems in the Northwestern IGP of India

The states of Punjab and Haryana in the Northwestern IGP of India are popularly known as the 'rice bowl' and 'breadbasket' of India (Dhillon et al., 2010; Chauhan et al., 2012). Rice yield gaps in this region were small, accounting on average to 2.7 t ha^{-1} for an average Yp of 9.8 t ha^{-1} corresponding to a yield gap closure of 70–80% of Yp (Fig. 6B), an often-quoted level of yield gap closure for high-yielding cropping systems (Silva et al., 2021b; van Ittersum et al., 2013; Lobell et al., 2009). A similar level of yield gap closure, i.e., 70–80% of Yp, was observed for intensive rice cropping systems in Southern Vietnam (Stuart et al., 2016) and in parts of China (Deng et al., 2019). Rice yields in the Northwestern IGP are close to the potential yield due to favorable alluvial soils and weather conditions for rice cultivation and high levels of inputs applied (Bhandari et al., 2017; Bhatt et al., 2021), particularly irrigation water and N fertilizers (Fig. 5A and 5B; Koshal, 2014). The latter is made possible through policies subsidizing and promoting the use of electricity and fertilizers to farmers. Our data also showed that there were no major differences in rice yield and input use across the districts covered by the field survey.

The small rice yield gaps in the Northwestern IGP of India were mostly explained by the technology yield gap (10–20% of Yp; Fig. 3). The efficiency yield gap explained on average 5% of Yp, whereas the resource yield gap was negligible across most districts. These findings are consistent with those found for intensive arable crops in the Netherlands (Silva et al., 2017b) and are to be expected in high-yielding cropping systems such as those studied here. Small resource yield gaps are the result of high use, and sometimes overuse, of inputs as shown here for the case of N applied (Fig. 6). Small efficiency yield gaps indicate that current technologies and management practices allow most farmers to manage inputs efficiently in relation to the time, space and form of inputs applied (cf. Fig. 6 and Suppl. Fig. S1). Yet, there is scope for improvement, for example to fine-tune the timing of the 2nd top dress

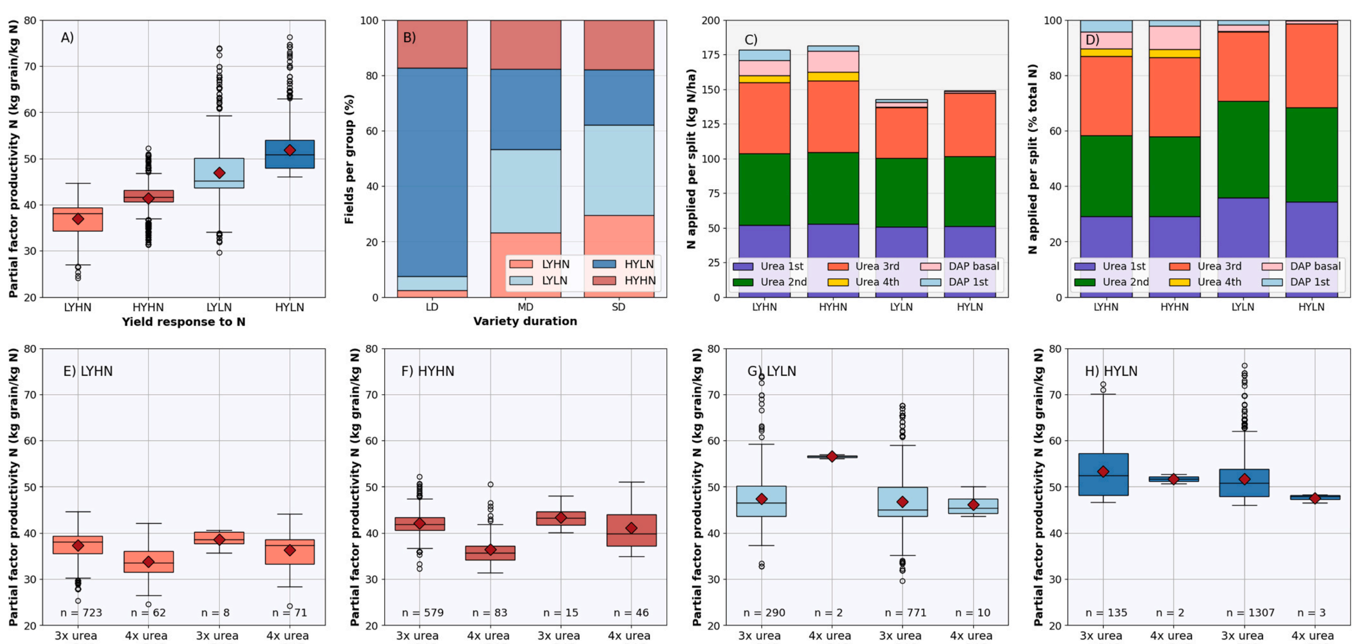

Fig. 6. N-use efficiency assessment for rice in the Northwestern Indo-Gangetic Plains of India during the 2020 *kharif* season: (A) Variability in N partial factor productivity (PFP-N) across different PFP-N groups; (B) Proportion of PFP-N groups for different variety type; (C) Average amount of N applied per N split for different PFP-N groups; (D) Proportion of N applied per N split to total N applied for different PFP-N groups; (E)-(H) Variation in PFP-N across PFP-N groups based on different combinations of N splits and fertilizer types. Codes: HYHN = fields with high yield and high N applied; HYLN = fields with high yield and low N applied; LYLN = fields with low yield and low N applied and, LYHN = fields with low yield and high N applied, LD = long-duration, MD = medium-duration and SD = short duration.

of urea as well as the timing of the 1st application of most plant protection products (cf. Table 2). Large technology yield gaps in high-yielding cropping systems are most likely the result of management imperfections in relation to pests and diseases (Buresh et al., 2021), which are challenging to overcome in larger commercial fields with less intensive day-to-day observation and management by farmers. Other factors not controlled for in our analysis, including micronutrient deficiencies or herbicide resistant weeds (Bhatt et al., 2016, 2021), or the lack of adoption of land levelling and other precision agriculture technologies (Aryal et al., 2015), might also explain the technology yield gap for rice in the Northwestern IGP of India.

The biophysical and management determinants of rice yield variability in our study were identified using stochastic frontier analysis. The quadratic response from applied N fertilizers (negative response after a plateau) and declining N partial factor productivity with increased N application rates suggest there is scope to improve NUE. Minimum and maximum temperature had a significant negative and positive effect on rice yield, respectively. It is well-known that rice yield declines with increases in minimum temperatures, which have been linked to higher physiological maintenance respiration with increases in minimum (night) temperature, which can reduce the accumulation of assimilates and affect yield (Peng et al., 2004). The strong negative effect of rainfall on rice yield might be explained by lower amounts of radiation intercepted with increases in rainfall.

Regarding crop management practices, the effects of number of tillage operations, sowing date, variety type and management of pests, diseases, and weeds (e.g., seed treatment, amount of plant protection products applied and weed control method) on rice yield were clearer than those associated with water and nutrient management. Rice yield was also affected by interactions between crop management practices (Table 2). For instance, rice yield response to N applied increased with the number of irrigations whereas rice yield response to P applied decreased with the number of irrigations. The former is expected because irrigation helps mobilizing free nitrate in the soil and favors uptake of N through transpiration driven mass flow and diffusion (Plett et al., 2020) whereas the latter might be the result of greater indigenous soil P availability under saturated conditions (Ponnamperuma, 1972). Similar to (Silva et al., 2017a), rice yield response to N applied increased with lower amounts of herbicide due to lower weed infestation level when herbicide applications were also lower (data not shown). As weeds compete for nutrients, radiation, and water with crops (Blackshaw et al. 2005), their presence can hamper crop yield responses to N if they are not adequately managed (Gholamhoseini et al., 2013). Similarly, a greater response to N and Zn was observed where herbicide application was lower; this is a proxy of lower weed infestation levels (data not shown).

4.2. N management and sustainable rice production

The small yield gap observed for *kharif* rice in the Northwestern IGP of India indicates little scope to further increase rice yields and hence, that opportunities to improve the economic and environmental sustainability of rice cropping in the region must also be considered. Judicious N management is essential to balance the economic and environmental performance of cereal cropping systems (Sapkota et al., 2020; Parihar et al., 2017b, 2017a). Currently, the Government of India subsidizes 75% of the production cost of urea, meaning that inefficient N management is indirectly associated with considerable risk of economic losses at national scale (Ministry of Chemicals and Fertilizers, 2016). From an environmental perspective, the application of 100 kg of N can also result into emission of about 1.2 kg of N in the form of N_2O from the soil (Albanito et al., 2017). As the NUE of India is one of the lowest in the world (Farnworth et al., 2017), it is indispensable to improve NUE of Indian agriculture, particularly in regions with high N use (Ladha et al., 2020), such as the Northwestern IGP. The latter must be linked with a reduction of the N surplus (i.e., the difference between N input and N output), which is also high in the states of Punjab and Haryana (Maaz et al. 2021). Improving NUE and reducing N surplus in situations where both N input and N output are high requires reductions in N input, without compromising N output (Silva et al., 2021a). The small rice yield response to N applied (Table 2), the similar N rates across highest-, average- and lowest-yielding fields (Fig. 5B), and the declining PFP-N with increased N application (Fig. 6) observed in this study suggest that there is scope to improve NUE in the Northwestern IGP of India by reducing N rate. The simple fact that many fields had more N applied than observed in highest-yielding fields indicates it is possible to reduce N application rates without compromising rice yields.

Our results showed that farmers adopting long-duration varieties managed N more efficiently than those adopting medium- and short-duration varieties (Fig. 6B). Long-duration varieties have greater yield potential than medium- and short-duration varieties and hence, require greater N application rates and the sustained supply of N over longer periods. Yet, the N application rates reported by farmers in our dataset were not tuned to the type of variety cultivated, which results in differences in PFP-N across variety types (Fig. 6B). Excess N application is associated with yield decline under some circumstances and a potential reduction in grain quality due to increased pest and disease pressure, lodging or induced soil acidity over time (Cassman and Harwood, 1995; Guo et al., 2010; Ogoshi et al., 2020). Increasing PFP-N in fields with medium- and short-duration varieties is possible (e.g., Fig. 6D), yet it requires smaller N application rates than currently observed for those variety types. Fine-tuning the source of N fertiliser and the number of fertiliser splits can also contribute to increased NUE for rice in the Northwestern IGP. For instance, a 4th urea split later in season could have been saved in some of the fields surveyed (Fig. 6 and Supplementary Fig. 1). The amount of N applied in the 3rd urea split should be also attuned to the amount of basal DAP applied to satisfy crop requirements of P while considering the addition of N (Fig. 6C–6H). Timelier N management also seems to be possible given the large variation observed in fertiliser application dates (Supplementary Fig. 1), which can contribute to improve N-use efficiency through narrowing efficiency yield gaps (Table 2).

4.3. Harnessing data from farmers' fields to inform sustainable intensification

Declining ground water levels, deteriorating soil quality, reductions in resource-use efficiencies, herbicide resistant weeds, and the threat climate change are the major sustainability issues and production constraints for rice production systems in much of the intensively cropped areas of the IGP India (Bhatt et al., 2021, Chauhan et al., 2012). Traditional agronomic research conducted on-station is primairly focused on testing alternative management practices and improved technologies for rice production through manipulative experimentation (Jat et al., 2019; Jat et al., 2020). On-station experiments, however, cannot easily account for the large number of management configurations and potential effects of environmental heterogenity that is typically observed in farmers' fields. Moreover, the technologies performing best on station might not be easily adopted by farmers due to resource constraints or other barriers that prevent their uptake. Conversely, as demonstrated in this paper, large databases of farmer field data coupled with spatially-explicit biophysical data can be used to assess a wide range of management practices and their interaction with environmental factors in a comparatively cost-effective way (Cassman and Grassini, 2020). In particular, this approach helped inform what appear to be more appropriate N management practices given the farmers' production conditions and resource constraints (e.g., Fig. 6).

This study focused on rice yields and yield gaps as well as on sustainable N use. Future studies should also assess the sustainability of crop production across scales based on multiple criteria relevant for farmers and stakeholders at large (e.g., Devkota et al. 2019, Silva et al., 2018). The latter include energy-use efficiency, greenhouse gas emissions, profitability, and other socio-economic aspects influencing labor productivity and the gender appropriateness of management practices. Farmer field data can also be used to rank farmers based on multiple criteria and to make explicit to policy-makers what synergies and tradeoffs between the different indicators might exist. Finally, assessments at the crop level, as presented here, must be complemented with assessments at the cropping systems level (Guilpart et al., 2017). This will aid in capturing the interactions between different crops in the cropping sequence, which is of critical importance for the sustainable intensification of rice-wheat cropping systems in South Asia.

5. Conclusion

A large database of farmer field data characterizing rice cultivation in the Northwestern Indo-Gangetic Plains (IGP) of India was used to estimate and decompose rice yield gaps and to assess the scope for sustainable intensification through improved resource-use efficiency in the region. Rice yield gaps in the Green Revolution corridor of Punjab and Haryana were small, in the range of 20–30% of the potential yield – a feature of high-yielding cropping systems. Most of the existing yield gap was explained by the technology yield gap (10–20% of the potential yield), whereas efficiency and resource yield gaps were small (less than 10% of the potential yield). The technology yield gap relates to management imperfections in relation to pests and diseases, and to other factors not controlled for in our analysis such as the adoption of precision agriculture technologies. The small resource yield gap is the result of high use, and sometimes overuse, of inputs. The small efficiency yield gap indicates that there is little scope to improve crop management in terms of the time and form of inputs applied. Yet, it is questionable whether rice yield gaps should be further narrowed given economic and environmental considerations for farmers. For instance, the small yield gap observed in this study was associated with high N application rates and with a small yield response to N applied and to irrigation number. There is thus considerable scope to improve NUE in this region, particularly by attuning N application rates to the crop variety being grown, by adjusting the amount of subsequent urea split to the amount of basal DAP applied, and by saving a 4th urea application later in the season. Future studies should assess the scope to reduce irrigation water, and increase water productivity and energy-use efficiency, and broaden the current sustainability assessment to other indicators related to profitability and environmental issues at the cropping systems level.

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.

Acknowledgements

This research work was carried out by International Maize and Wheat Improvement Centre (CIMMYT) and ICAR-Central Soil Salinity Research Institute (CSSRI), Borlaug Institute for South Asia-CIMMYT within the CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS; https://ccafs.cgiar.org), with the funding support from CGIAR Fund Donors and through bilateral funding agreements. For details of CCAFS donors, please visit https://ccafs.cgiar.org/donors. Portions of this work were also supported by the USAID and Bill and Melinda Gates Foundation (BMGF) supported Cereal Systems Initiative for South Asia (https://csisa.org) The first author sincerely acknowledges the Indian Council of Agricultural Research (ICAR), ICAR-Indian Agricultural Research Institute (IARI), Director, ICAR-IARI, New Delhi, and Division of Agronomy, ICAR-IARI, New Delhi for their support in providing the opportunity to complete the Ph.D. research work with CIMMYT. We acknowledge Gokul Paudel, Saral Karki and Asif Faisal, Sanjay Pothireddy and Noufa Cheerakkollil Konath for technical assistance and Manish Kumar, KM Choudhary, Yogesh Kumar, Love K Singh, Sushil Kumar, Kailash Kalvania for help during data collection. This manuscript should not be taken as endorsement by CCAFS, USAID or the US government, or BMGF, and shall not be used for advertising purposes.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.fcr.2021.108328.

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