Agricultural Systems 192 (2021) 103182

Contents lists available at ScienceDirect

Agricultural Systems

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

Coupling landscape-scale diagnostics surveys, on-farm experiments, and simulation to identify entry points for sustainably closing rice yield gaps in Nepal

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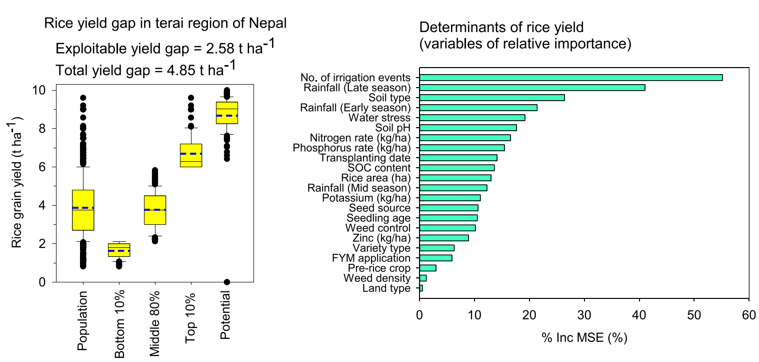
HIGHLIGHTS

- Mixed-method approach used to decompose rice yield gaps with landscape-scale surveys, on-farm experiments, and modeling.
- Sizeable exploitable (2.58 t ha^{-1}) and total yield gaps (4.85 t ha^{-1}) were documented across the Terai of Nepal.
- Principal drivers of yield outcomes include irrigation intensity, rainfall, nitrogen and phosphorus fertilizers.
- Top-yielding farmers had lower GHG emission intensities (43%) with increased water and nutrient use efficiencies.
- Transformative rice yield (1.86 t ha^{-1}) and profitability (US$ 243 ha^{-1}) gains were achieved by ‘good agronomic practices’.

GRAPHICAL ABSTRACT



ARTICLE INFO

Editor: Dr Jagadish Timsina

Keywords:
Yield gap
Sustainable intensification
Machine learning
Sustainability indicators
Good agronomic practices

ABSTRACT

CONTEXT: Rice is the primary staple food crop in Nepal, contributing 20% of the agricultural gross domestic product and more than 50% of the total calories in the national diet. Nevertheless, the productivity of rice (3.36 t ha^{-1}) is the lowest in South Asia region.
OBJECTIVE: The objective of this study was to employ a mixed-methods approach to characterize and decompose yield gaps (YGs) in the context of identifying sustainable intensification pathways for rice production in Nepal.
METHODS: Methodologies include: a) landscape-scale crop diagnostic survey on crop management, field attributes, and productivity outcomes combined with gridded soil and daily weather data to decompose rice yield gaps into constituent factors with machine learning diagnostics; b) with survey data, computation of key performance indicators to identify factors associated with productivity, profitability, and resource use efficiencies; c) complementary multi-location on-farm experiments (2011–2017) evaluating new agronomic management practices; and d) dynamic simulation (ORYZA3) to derive estimates of rice yield potential.

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https://doi.org/10.1016/j.agsy.2021.103182
Received 1 December 2020; Received in revised form 13 May 2021; Accepted 15 May 2021
Available online 25 May 2021
0308-521X/

RESULTS AND CONCLUSIONS: Analysis of survey data suggests an exploitable YG of 2.57 t ha^{-1} (40%) and the total YG of 4.85 t ha^{-1} (55%) indicating substantial scope for increasing rice yields in Nepal. Frequency of irrigation, amount of late-season rainfall, soil type, amount of early-season rainfall, presence of water stress, soil pH, and nitrogen (N) and phosphorus (P) fertilizer rates are the principal determinants of productivity outcomes in descending ranked order. Efficiency metrics suggest rice farmers in the study region make good use of fertilizer inputs, but since application rates are very low (e.g. most farmers apply <20 kg P ha^{-1}) unsustainable mining of soil nutrients is likely common. Farmers in the top 10% of the yield distribution had lower greenhouse gas emission intensities (−43%), increased water productivity (+66%), and higher use efficiencies of N and P fertilizers (+28% and + 20%, respectively), suggesting that yield intensification can be achieved without tradeoffs with key environmental performance indicators. On-farm experiments conducted over several seasons support insights from surveys by demonstrating that major gains in rice yield (1.86 t ha^{-1}) and profitability (US$ 243 ha^{-1}) are achievable through the adoption of good agronomic practices.
SIGNIFICANCE: Through a mixed methods approach, our results suggest that adoption of integrated 'good agronomic practices' can close YGs and improve food security outcomes associated with the rice-based agricultural systems of Nepal while simultaneously preserving or enhancing key sustainability and livelihood objectives.

1. Introduction

Rice (*Oryza sativa* L.) is the principal staple crop in Nepal. It is grown in diverse production conditions ranging from tropical plains of the Terai region to mountain terraces at elevations up to 3050 m above sea level. Approximately 70% of the total rice production is in the Terai region (CBS, 2019). Rice alone contributes nearly 20% to agricultural gross domestic product and supplies more than 50% of the total caloric intake. Compared to other neighboring countries, like India (3.9 t ha^{-1}), Bangladesh (4.7 t ha^{-1}), China (7.02 t ha^{-1}), and Pakistan (3.84 t ha^{-1}), the productivity of rice (paddy) in Nepal is the lowest in the region (3.36 t ha^{-1}) (FAOSTAT, 2021). Before 1980, Nepal was an exporter of rice but thereafter it became a net importer with the cost of imports rising to US$ 270 million in 2016 (Pudasainee et al., 2018). Increased rice imports are associated with other structural changes in Nepal's economy including increasing labor wage rates fueled by out-migration and associated profitability reductions in rice cultivation (Bhandari et al., 2015). The current average annual growth rate for rice yield in the country is approximately 1%, which is lower than the population growth rate (FAOSTAT, 2021). Rice demand has further been increasing due to dietary shifts associated with urbanization and increasing road accessibility connecting rural villages with larger markets. Together, these factors strongly suggested an opportunity to reinvigorate rice productivity growth in a manner that enhances sustainability.

The Nepal Government has formulated various policies and national programs that address the intensification of rice production, including the Agriculture Development Strategy (ADS) 2015–2035, National Seed Vision, 2013–2025, and the Prime Minister Agriculture Modernization Project (PMAMP) (MoALD, 2020). While it is premature to judge the success of these initiatives, many of the technologies and management approaches that have been prioritized are incompletely supported by scientific evidence and, even where evidence is comparatively strong, multi-dimensional assessment of productivity, profitability, and sustainability are often lacking. To help close knowledge gaps with national partners in the public and private sector, the Cereal System Initiatives for South Asia (CSISA, https://csisa.org) was initiated in Nepal in 2009 to assist these partners to sustainably enhance the productivity and profitability of cereal systems.

Yield gap (YG) analysis provides a framework for contextualizing current farmers' yields against potential yields in different production environments (van Ittersum et al., 2013). Various methods can be used to estimate crop yield potential including dynamic simulation and controlled-condition field experiments (Devkota et al., 2019a; Lobell et al., 2009; Rhebergen et al., 2018; van Ittersum et al., 2013). Nevertheless, YG analysis is of limited use for intervention prioritization for agricultural development if the multiple causes for lower farmer productivity are not identified; i.e. YG must 'decomposed' by their constituent factors (Devkota et al., 2015, 2016; Lobell et al., 2009). Controlled on-farm experiments offer a conceptually straightforward approach for assessing the value of agronomic interventions, but results cannot be generalized in complex crop production environments where management and resource factors vary widely at the landscape scale (e.g. in Nepal). As a complement to on-farm research, diagnostic surveys can efficiently capture major drivers of farmer exploitable yields across environmental and management gradients but are less adept at assessing potential contributions of new technologies and management practices that are not yet practiced at scale by farmers. Further, both on-farm experiments and diagnostic surveys have limited capacity to understand the influence of dynamic climate factors on yield and yield stability. Hence, dynamic simulation models can provide a useful complement to YG studies in production ecologies like rice-wheat systems in Nepal where inter-annual climate variability is high and resource-poor farmers, in general, exert less control over the environment through practices like ample irrigation and timely crop establishment. In many circumstances, conjunctive use of all three approaches is likely needed to understand YGs and their factor-based constituents.

The concept of 'sustainable intensification' aims to achieve or maintain high levels of crop productivity while reducing environmental damage, building resilience, ensuring essential ecosystem services, and improving rural livelihoods by enhancing profitability (The Montpellier Panel, 2013). In practice, this implies that gains in productivity have to be accompanied by efficient use of all resources, including land, labor, water, energy, and other critical inputs like mineral fertilizers and agrochemicals (Rockström et al., 2017). To ensure that potential rice yield gains support broader sustainable development goals, the objectives of this study were to 1) determine rice YGs and YG drivers with a mixed-methods approach combining diagnostic surveys and machine learning with on-farm experiments and dynamic simulation modeling; 2) assess the contributions of different agronomic interventions to close YGs; 3) understand the economic (gross margin) and environmental (nutrient use efficiencies, water productivity, estimated greenhouse gas emissions) dimensions of yield intensification.

2. Materials and methods

2.1. Study sites

The CSISA project has activities across eight Terai districts (Fig. S1). The study sites have sub-tropical, warm, and humid climatic conditions with a wet monsoon season ('kharif'; May through September) followed by a long dry season marked by cooler temperatures (October through March). The average annual maximum temperature is 30.6 °C, the minimum temperature 18.8 °C, and the mean solar radiation is 15.8 M J m^{-2} d^{-1} (Fig. S2). In these Terai districts, 89% of the mean total rainfall (1566 mm) occurs from May 1st to September 30th.

2.2. Diagnostic survey

2.2.1. Sampling framework

The sample (location and household) for the rice landscape diagnostic survey was determined using remote sensing-based normalized difference vegetation index (NDVI) values derived from Landsat images at a spatial resolution of 30×30 m^2. Images were analyzed from the 4th week of August 2016, when rice was anticipated to be at or near maximum seasonal NDVI. To guide sampling within each of the six target districts, the mean, standard deviation (SD), minimum and maximum value for each district were computed (Fig. S3). Sampling locations for each district were selected based on a proportionate method assuming a normal data distribution. The gridded NDVI values were first stratified into four quartiles and samples were drawn randomly within each quartile. Using this approach, a total of 1052 production plots were selected (48, 48, 24, and 24 on two sides of the curve, i.e., mean NDVI $\pm$1 SD, and mean $\pm$ 2 SD) from each district for the diagnostic survey.

2.2.2. Data collection

For the fields identified through Landsat, a diagnostic survey was implemented to collect data using a semi-structured questionnaire designed to capture rice management practices, site characteristics, basic socio-economic information, and farmer-reported crop yields from the 2016 rice season. The survey was carried out on a digital platform (open data kit; ODK) and the geo-location of each plot was recorded (i.e., latitude and longitude). Farmers were asked about the timing of all major field operations, methods used for crop establishment, the variety planted as well as seedling age at transplanting, the amount and timing of all organic and inorganic fertilizer inputs, the number of irrigation events, and pest and disease control measures. Farmers were also asked for visual observation on crop stress due to water, weeds, diseases, and pests. The entire dataset and codebook are available through the CIMMYT data repository: https://data.cimmyt.org/dataset.xhtml?persistentId=hdl:11529/10968.

2.2.3. Computation of production parameters used and economic and environmental sustainability indicators

Crop production parameters for example amount of farm-yard manure (FYM) and chemical fertilizers (N, P, K, and Zn), amount of water (irrigation + rainfall), planting and harvesting time, variety, seed source, seedling age, and crop maturity duration were computed across districts. To assess the broad-based performance of the surveyed rice fields, seven economic and environmental indicators were estimated for each six surveyed districts and three yield category (mean of bottom 10, middle 80, and top 10%) farmers. These seven indicators includes: (1) grain yield; (2) gross margin, (3–5) nitrogen-, phosphorus-, and potassium-use efficiencies (NUE, PUE, and KUE); (6) water productivity; and (7) greenhouse gas (GHG) emissions intensity (GHGI). Grain yield was computed from the farmers' reported yield from the largest plot based on sun-dry weight. As the questionnaire in this survey was not designed to assess profitability, we used secondary literature from the same region combined with key informant surveys, government fixed price policies, and input price recall interviews to compute gross margin (profitability) for the surveyed farms (Table S1). Gross value was computed considering per kg grain price of US$ 0.19 (the government price validated with the market price at that time and exchange rate of US$ 1 = Nepalese rupees of 105), straw price of US$ kg^{-1} 0.026, and harvest index of 48% (IRRI, 2004). The cost of production was calculated from the inputs (seed, chemical, and FYM fertilizers, irrigation, herbicide) and total labor and machinery used (for land preparation, crop establishment, harvesting, threshing, drying, and cleaning) (Table S1). The gross margin was computed by subtracting the total production cost from the gross value including grain and straw. Production cost also includes the imputed value of the family labor but excludes land rental charges and fixed costs like machinery since these could not be estimated based on survey data. The NUE, PUE, and KUE were determined only for those farmers who applied these fertilizers and were calculated as partial factor productivity (kg grain per kg nutrient) of N, P, and K by dividing the reported grain yield by the kg of respective nutrient applied. Most farmers in Nepal maintain livestock and FYM application to soil is a standard practice in the study area. It is difficult to estimate nutrient additions from FYM since dry weight nutrient concentrations of FYM vary widely as does the moisture content. For the purposes of our study, we treat FYM as part of the indigenous nutrient pool that has an intrinsic effect on fertilizer use efficiency and, hence, did not include FYM in the nutrient use efficiency calculations. Water productivity (kg paddy L^{-1}) was computed by dividing the amount of grain yield by the total amount of water input (irrigation +rainfall). For each farmer, from the total number of irrigation events and the average depth of irrigation (70 mm per irrigation event; validated from key informant) (Table S1) the amount of irrigation water applied was estimated according to the methodology used by Devkota et al. (2020). The daily rainfall estimates were obtained from the grided CHIRPS data (Funk et al., 2015).

Yield-scaled GHG emissions (GHGI) (Eq. 1) expressed in CO_2-equivalents was computed from a combination of direct (CH_4, N_2O) and indirect (energy used for fertilizer manufacture) sources. The CO_2 equivalent emissions from methane due to water management were computed using a formula described by IPCC (Devkota et al., 2019b; Devkota et al., 2020; Dong et al., 2006; Stuart et al., 2018). Direct GHG emissions were computed applying the formula provided by Cui et al. (2013) and the indirect emissions were computed using the methodology as described by Wu et al. (2014). The results were expressed in yield-scaled GHG emission intensity (GHGI; kg CO_2 equivalent emissions t^{-1} grain) (Pittelkow et al., 2014; Sainju et al., 2014; Snyder et al., 2009). Details of all equations used for the GHGI calculation have been described in Supplementary Information (Appendix I).

$$\text{Greenhouse gas emisison intensity (GHGI)} = \frac{\text{Total CO2 equivalent emission (kg)}}{\text{Paddy grain (t)}} \tag{1}$$

2.2.4. Machine learning analytics

Random Forest (RF) analysis develops an ensemble of regression or classification trees where individual trees are constructed from a random sub-sample of both predictor variables and observations (i.e. bagging) (Breiman, 2001; Breiman and Cutler, 2012). We employed the 'randomForest' package in R Version 4.0.2 to identify yield determinants (based on relative importance, i.e. %IncMSE metric – see Breiman and Cutler, 2012) based on the survey and environmental characterization data described in section 2.2.3. Twenty-two yield predictor variables were used, including: soil factors (organic carbon (SOC), pH, texture), inputs (seed, fertilizer, irrigation events, variety), crop establishment (seedling age, transplanting date), weed density, abiotic factors (crop-water stresses), and seasonal rainfall amount i.e., early- (Jun 1-Jul 15), mid- (Jul 16-Aug 30), and late- (Sep 1-Oct 15) rainfall (Table S2). We used gridded datasets to estimate environmental factors at each surveyed location, including CHIRPS for rainfall (Funk et al., 2015) and WISE for soil attributes (Batjes, 2012). The RF model was trained by using 80% of the data with 20% reserved for independent model validation. To understand the geographic dependencies of yield predictors, we ran the RF model for the combined data from six districts and also for individual districts. Partial dependence plots (PDP) were constructed for assessing the relationship between crop yield (response variable) with the variations in single features (e.g. fertilizer rate, irrigation event) (Friedman, 2001; Hastie et al., 2009).

2.3. On-farm experiments

The prevailing wisdom in Nepal suggests that poor seedling health, late transplanting, use of older cultivars, and a lack of integrative

Table 1
Detail crop management practices adopted in the on-farm experiments during 2011–2017 in eight Terai districts.

Exp No.	Experiment	Total no. of paired experiments	Districts	Year of implementation	Varieties	Treatment	Farmers practice (FP; control)
I	Rice nursery: (Healthy seedling vs. FP)	48	Bardiya, Banke, Rupandehi	2017	commercially grown varieties	Seedling age less than 22 day; seed rate of 1 kg seed per 10 m^2 nursery area, 60:40:30 kg N:P:K fertilizer, and dry-raised bed nursery	Seedling age 30–40 days; 1 kg seed in 20–30 m^2 area; no chemical fertilizer, and flat wet-bed nursery in puddled field
II	Transplanting time: (Timely vs. late transplanting	198	Kanchnapur, Kailali, Bardiya, Banke	2011, 2014–2016	Commercially grown varieties	Before 15 June in Kailali and Kanchanpur and before 15th July in other four districts	After June 15 in Kailali and Kanchanpur and after 15 July in other four districts
III	Varieties: (Hybrid vs. improved)	174	Kanchnapur, Kailali, Bardiya, Banke	2015–2016	–	Gorakhnath, Bioseed-786, Loknath, Shankar, Muskan, Bioseed-786, Arize-6444	Radha-4; Samba Masuli, Sabitri
IV	Agronomic practices (Good agronomic practices; GAP vs. farmers practice; FP)[1]	83	Kanchnapur, Kailali, Bardiya, Banke, Rupandehi	2017	Commercially grown varieties (Arize-6444 and Radha-4)	Healthy nursery; line transplanting at 20 × 20 cm spacing; fertilizer rates (100:30:30 kg N:P:K ha^{-1}); supplemental irrigation (when required); and timely weed management	Conventional method of nursery raising and transplanting; fertilize rate (50–100 kg N:10–20 kg P: 0 kg K ha^{-1}; mostly rainfed; late weed management (after 50 days after transplanting)

[1] Note: In experiment IV, there were two farmers practice. The compared here together is FP1.

agronomic management are all factors constraining rice yield and profitability. Sub-optimal nursery management (i.e., use of old seedling, no fertilizer, dense planting, poor water management) is common in the Nepal Terai (CSISA, 2017). Poor seedbed management can cause significant yield losses as has been reported by Balwinder-Singh et al. (2019), Lampayan et al. (2015), and Sarangi et al. (2015). Similarly, rice transplanting date is often delayed by the late onset of monsoon rains, a scenario that exacerbates the risk of late-season drought and significant yield losses (Balwinder-Singh et al., 2019; Cornish et al., 2015; Devkota et al., 2019b; Kumar and Ladha, 2011). Rice production and profitability can be increased through the use of high-yielding improved medium and short-duration hybrid varieties (Anwar et al., 2021). Further, integrative agronomic practices can offer transformative gains in yield, resource use efficiency, and profitability (Stuart et al., 2017, 2018). To validate these assumptions in the Nepal Terai, four different types of on-farm experiments were conducted: (1) healthy vs. farmers' practice of raising seedlings, (2) timely vs. late transplanting, (3) hybrid vs. improved variety, and (4) good agronomic practices (GAP) vs. farmer crop management practices (FP). Paired (treatment vs. control) on-farm trials were conducted on 503 farms in 30 different locations across eight Terai districts (Banke, Bardiya, Kailali, Kanchanpur, Nawalparasi, Rupandehi, Dang, and Kapilbastu) over a seven-year period (2011–2017) (Fig. S1). Details of these experiments and treatments have been presented in Table 1. Plots were selected for experiments based on farmers' willingness to participate and also the availability of irrigation.

In general, the experimental area is characterized by clay to sandy loam soil. The soil organic carbon content ranged from 0.6 to 1.28% (Walkley and Black, 1934), pH of 6.7–7.06, and a bulk density of 1.4 to 1.5 g cm^{-3} (Devkota et al., 2019b; LRMP, 1986). Unless noted (Table 1) and excepting experimental factors, all trials were conducted with established 'good' agronomic practices (so-called GAPs, i.e. improved variety, healthy seedlings, recommended fertilizer rate, timely weed management, supplemental irrigation as needed to avoid moisture stress). Rice was established by transplanting in puddled soil (PTR) in a grid pattern at 20 × 20 cm spacing. Individual plot sizes ranged from 330 to 2000 m^2. Training on GAP practices was provided to farmers before the start of the trials and periodic guidance and oversight given by research technicians over the course of the growing season.

To estimate the grain yield from all on-farm experiments, the crop was manually harvested from three areas (diagonally dividing the experimental plots into three equal sections and selected harvest area from the center of each section) in each plot covering 4 m^2 and converted to yield (kg ha^{-1}) at 13% moisture content. Both yield and gross margin were computed in the 4th (GAP vs. FP) experiment, considering total production cost and total income (straw + grain). The input cost (seed, fertilizer, labor, herbicides, and irrigation water) and output price (grain and straw) were derived from a local market survey for each district.

2.4. Simulation of climatic potential yield

Potential yield (i.e. non-limiting water and nutrients) was simulated with the ORYZA3 model for six western Terai districts (Kanchanpur, Kailali, Bardiya, Banke, Kapilbastu, Rupandehi), where landscape diagnostic household surveys were conducted. The rice variety used for potential yield simulation is a widely grown variety that is common in all Terai districts ('Sabitri', an improved inbred variety with 140 days maturity) and was seeded on June 15 from 1987 to 2017. For the model calibration (Fig. S4A), the genetic coefficients of variety 'Sabitri' were derived running the DRATE1 module of ORYZA3 using experimental data from three seeding dates (with three replication) experiments conducted in the National Wheat Research Program (NWRP), Rupandehi during 2012–2013. During the calibration process, the coefficients for development rate in the juvenile phase (DVRJ), photoperiod-sensitive phase (DVRI), panicle development phase (DVRP); and reproductive phase (DVRR) were computed (Table S3). The model was validated using independent data of the four N rates (0, 60, 120, 180 kg N ha^{-1}) experiment conducted under the PTR establishment method over two years (2012−2013) in two locations, i.e., Rupandehi and Parwanipur (Fig. S4B). The model was deemed capable of estimating potential yield since the ratio between simulated and observed yield, R^2, β and d-stat values were close to 1 (Li et al., 2015), α close to 0, $RMSE_a$ was similar to the standard error of the measured values, and $RMSE_n$ was similar to the coefficient of variation of the measured values.

2.5. Data analysis

The exploitable and the total YGs were derived for all six Terai districts. Based on yield from the survey, farmers were classified into three categories: top (mean of top 10%), middle (mean of middle 80%), and bottom (mean of bottom 10%). The exploitable YG was computed as the difference between the average yield of the top 10% of the yield distribution ('exploitable' yield) and the population mean yield. Percent exploitable yield gap was computed by dividing this difference by the

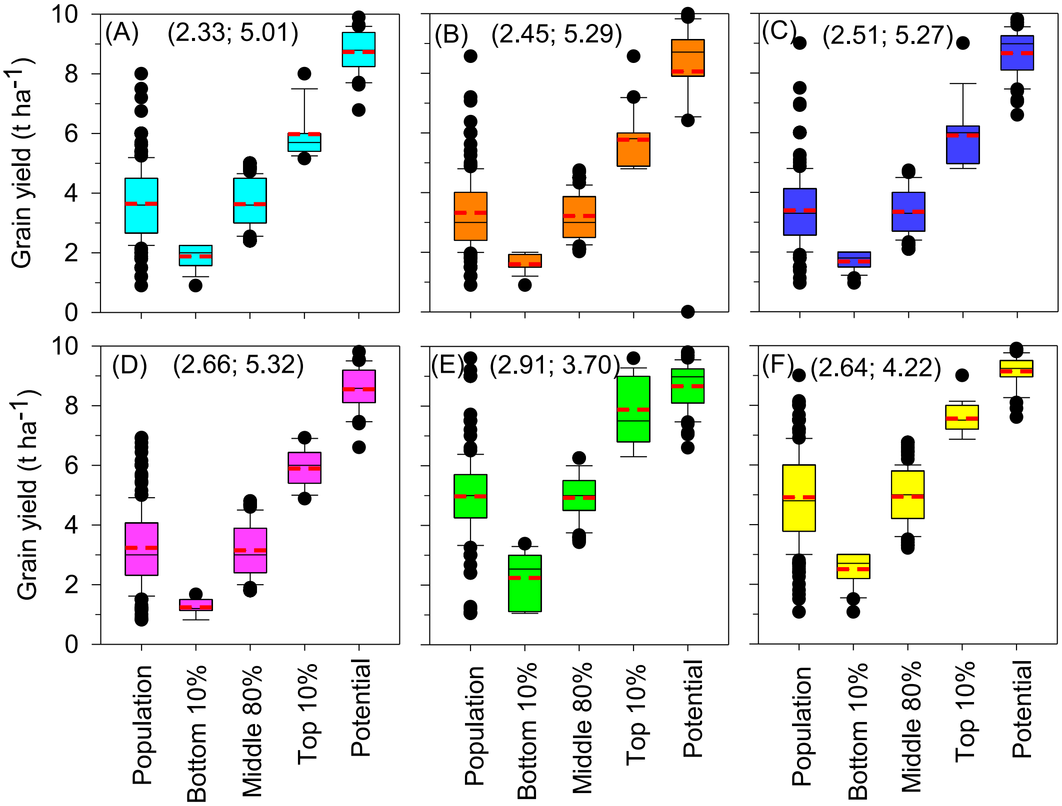

Fig. 1. Variation in exploitable and total yield gaps (t ha^{-1}) in rice in Kanchanpur (A), Kailali (B), Bardiya (C), Banke (D), Kapilbastu (E), and Rupandehi (F) districts from the farmers reported largest plot yield data from survey data and simulation using ORYZA3. Black solid line inside the box the median and the red dotted line the mean. Figures in parenthesis are the yield gaps (first value exploitable yield gap; and the 2nd value the total yield gap). The total yield was derived from long-term (1987–2017) simulation.

average yield of top farmers (Devkota et al., 2019b; Stuart et al., 2016). Similarly, the total YG was derived from the difference between the ORYZA3 simulated potential yield and the population mean from the surveyed farmers (total YG). Gross margins were derived for all surveyed households and also for the GAP and FP (on-farm experiment IV). For the quantification of the performance of integrated GAP practices (on-farm experiment IV), two methods for defining farmer practices (FPs) were employed: FP1 (adjacent paired comparisons with researcher instructed and monitored and farmer operated plots (see detail in Table 1) and FP2 (area averages from survey data). Target indicator values for enhancing yield, gross margin, and sustainability were computed from the difference of average value of the top 10% (target) and the population mean (baseline) for positive indicators (higher value is better), and vice versa for the negative indicators e.g. GHGI, where reductions indicate progress (Devkota et al., 2020).

Random forest regression model and PDPs (Breiman, 2001; Breiman and Cutler, 2012) were used to quantify the determinants (variable of relative importance) for yield variation in different spatial domains. PDP was used to quantify the marginal effect of individual inputs in yield (predicted outcome) variability. Yield responses to a few key categorical variables (e.g. water stress and soil type) are presented in boxplots. The upper and lower boundaries for NUE (100 and 30), PUE (300 and 100), KUE (300 and 50), respectively, were derived using the concept of nutrient output:input ratio to avoid scenarios of either nutrient loss (due to over-application) or nutrient mining (due to under-application) by adjusting those values as suggested by Devkota et al. (2019b), Dobermann (2000), and EU Nitrogen Expert Panel (2015) to the context of Nepal. Apparent trade-offs among sustainability indicators were evaluated as a function of irrigation (with vs. without supplementary irrigation), N rate (application rate above and below the population mean; ≥72 vs. <72 kg N ha^{-1}), variety (hybrid vs. improved variety), and land-

Table 2
Characterization of rice production inputs in population mean and three yield categories from household survey data 2016. Values shown different categories are mean ± SD.

Inputs used	Population	Bottom 10%	Middle 80%	Top 10%
Number of household surveyed	1052	117	809	126
Rice area per household, ha	0.80± 0.82	0.90± 1.04	0.79± 0.80	0.81± 0.72
Nursery establishment date	13 June±11	11 June±9	13 June±11	16 June±11
Harvesting date	30 Oct ± 14	30 Oct ± 11	30 Oct ± 14	5 Nov ± 15
Seedling age, day	27.4 ± 6.1	27 ± 6.6	27 ± 6.1	27 ± 5.9
Crop duration, day	140 ± 11.6	141 ± 10.4	140 ± 11.5	142 ± 13.1
Elemental N, kg ha^{-1}	72 ± 38.4	66 ± 45.9	70 ± 36.7	93 ± 35.1
Elemental P, kg ha^{-1}	21 ± 13.1	18 ± 15.2	20 ± 12.6	28 ± 12.3
Elemental K, kg ha^{-1}	2.8 ± 9.4	1 ± 5.3	2 ± 9.0	7 ± 13.2
Zinc Zn, kg ha^{-1}	0.8 ± 4.1	0 ± 2.0	1 ± 4.0	2 ± 5.7
Farm yard manure (FYM), t ha^{-1}	3.1 ± 8.5	2 ± 3.1	3 ± 9.5	3 ± 4.4
No. of fertilizer applied	1.6 ± 1.8	1 ± 1.6	2 ± 1.8	2 ± 2.3
No. of irrigation events	2 ± 1.2	2 ± 1.3	2 ± 1.2	2 ± 1.1

holding size (rice area less and more than the population mean area or < 0.44 vs. ≥0.44 ha). To analyze treatment effects of series of paired datasets from four different types of on-farm experiments (Table 1), comparisons were made between experimental (treatments) vs. control (FP) using paired *t*-test in the statistical software R Version 4.0.2. Descriptive statistics (mean and SD) are presented wherever applicable.

Table 3
Economic and environmental indicators of rice production in three yield categories and population from household survey data 2016. Values are mean ± SD.

Input parameters	Population mean (Baseline)	Bottom 10%	Middle 80%	Top 10% (Target)	Target value for improvement ¶
Economic indicators					
Total variable cost of production, US$ ha^{-1}	593 ± 82	532 ± 77	589 ± 75	678 ± 58	85
Grain yield, t ha^{-1}	3.88 ± 1.53	1.64 ± 0.37	3.76 ± 0.96	6.70 ± 0.92	+2.82
Gross margin, US$ ha^{-1}	307 ± 328	−151 ± 112	284 ± 223	877 ± 218	+570
Environmental indicators					
Water productivity, kg grain m^{-3} water	0.271 ± 0.11	0.122 ± 0.033	0.265 ± 0.078	0.449 ± 0.09	+0.178
Greenhouse gas emission intensity (GHGI), kg CO_2 equivalent emission t^{-1} grain	1097 ± 519	2202 ± 675	1010 ± 253	624 ± 94	−473
Nitrogen use efficiency (NUE), kg grain kg^{-1} elemental N	68 ± 49	36 ± 28	69 ± 46	87 ± 63	+19
Phosphorus use efficiency (PUE), kg grain kg^{-1} elemental P	238 ± 264	120 ± 87	247 ± 287	286 ± 176	+48
Potassium use efficiency (KUE), kg grain kg^{-1} elemental K	393 ± 466	172 ± 144	412 ± 525	391 ± 330	−2

¶ + indicate increment and – indicate reduction of each indicators for improving sustainability.

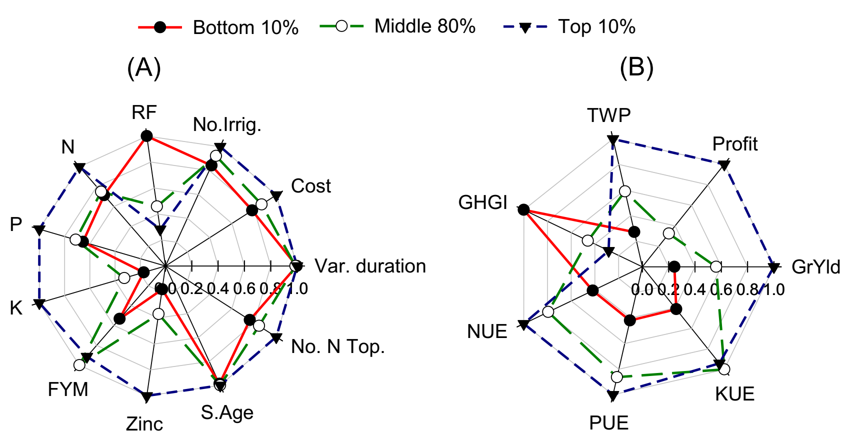

Fig. 2. Input use (A) and sustainability indicators (B) among three yield gap category farmers. Data from six surveyed districts. Symbols and units for inputs used (A): Var. duration = growing duration of a variety (d), Cost = variable cost of production (US$ ha^{-1}), No.Irrig = No. of irrigation events ($season^{-1}$); RF = amount of rainfall (mm $season^{-1}$); N = nitrogen fertilizer input (elemental N, kg ha^{-1}), P = phosphorus fertilizer input (elemental P, kg ha^{-1}), K = potassium fertilizer input (elemental K, kg ha^{-1}), FYM = farm yard manure (t ha^{-1}), Zinc = zinc fertilizer input (elemental P, kg ha^{-1}), S. Age = seedling age (days), No·N Top. = Times of N fertilizer topdressing.
Symbols and units for indicators (B): GrYld = grain yield (t ha^{-1}), Profit = gross margin from rice (currency US$ ha^{-1}), TWP = total water productivity (kg grain L^{-1} water (irrigation + rainfall), GHGI = greenhouse gas emission intensity (kg CO_2-equivalent t^{-1} grain), NUE = nitrogen use efficiency (kg grain kg^{-1} elemental N), PUE = phosphorus use efficiency (kg grain kg^{-1} elemental P), KUE = potassium use efficiency (kg grain kg^{-1} elemental K).

3. Results

3.1. Spatial variation in yield gaps, inputs use, and sustainability indicators

3.1.1. Rice yield gaps

The YG varied across the districts (ranging 35–45% exploitable and 43–62% total), with the mean exploitable YG of 2.57 t ha^{-1} (40%) and the total YG of 4.85 t ha^{-1} (55%). The highest exploitable YG was in Banke and the lowest in the Rupandehi district. Similarly, the highest total YG existed in Banke and the lowest in Kailali (Fig. 1).

3.1.2. Input use and sustainability indicators across three yield gap category farmers

Farmers at the lowest end of the yield distribution (<1.6 t ha^{-1} yield) applied the lowest amount of N, P, K, Zn, and FYM fertilizers followed by middle (3.8 t ha^{-1}) and top (6.7 t ha^{-1}) terciles (Table 2; Table 3; Fig. 2). The bottom yield category farmers lost money on rice whereas the top tercile had a gross margin of US$ 877 contrasted to a population mean of US$ 257, indicating the scope to increase gross margin by US$ 570 ha^{-1} and yield by 2.8 t ha^{-1} with the additional expense of US$ 85 (*n.b.* this approach does not account for the possibility that variations in rainfall contributed to favorable yield outcomes) (Table 3). With respect to sustainability indicators, the top-yielding tercile of rice fields had 43% lower GHGI with increased water productivity (66%) as well as increased efficiency of N and P fertilizers by 28% and 20%, respectively, compared to the population mean.

Similarly, a significant variation in input use and the indicators across districts and the yield category exists (Fig. S5). In all districts, yield, gross margin, NUE, and PUE (inconsistent in KUE as very low number of farmers applied), and water productivity were highest with top followed by middle and the lowest (with negative gross margin) with the bottom. The bottom had the highest GHGI followed by the middle, and the top, respectively.

3.1.3. Input use and sustainability indicators across Terai districts

Across the surveyed districts, the mean rice planting time was June, and the harvesting time was October (Table S4). The mean farm size varied across the districts, ranging from 0.5 to 1.1 ha. Rice nursery establishment and transplanting dates varied and earliest (by 25 days) in Kanchanpur and Kailali (far-western region) and delayed/late in Kapilbastu. The 29% of a surveyed farmers were growing hybrid, 63% improved, and 8% traditional cultivars. Average application rates (based on all farmers) were 72 kg N ha^{-1} (46 and 96 kg ha^{-1} Q1 and Q3, respectively); 21 kg P ha^{-1} (12 and 46 kg ha^{-1} Q1 and Q3); and 3 kg K ha^{-1}. In the region, 99% of farmers applied only N, 93% of farmers applied N and P, and 13% of farmers applied N, P, and K as mineral fertilizers. Farmers in Rupandehi applied the highest amount of fertilizers followed by Kapilbastu and the lowest in Banke district. Farmers in Kanchanpur applied the highest amount of FYM in their field. The average total water input during the rice season was 1456 mm with 113 mm from irrigation (average frequency of application 2.1 times) and 1343 mm from rainfall between 1st of June to 15th of October (Table S4).

Fertilizer use efficiencies varied across districts with mean NUE values of 68, PUE of 238, and KUE of 393 kg grain kg^{-1} elemental N, P, and K, respectively. The majority of farmers are likely mining soil nutrient stocks due to low application rates of N (<50 kg ha^{-1}; 33%), P

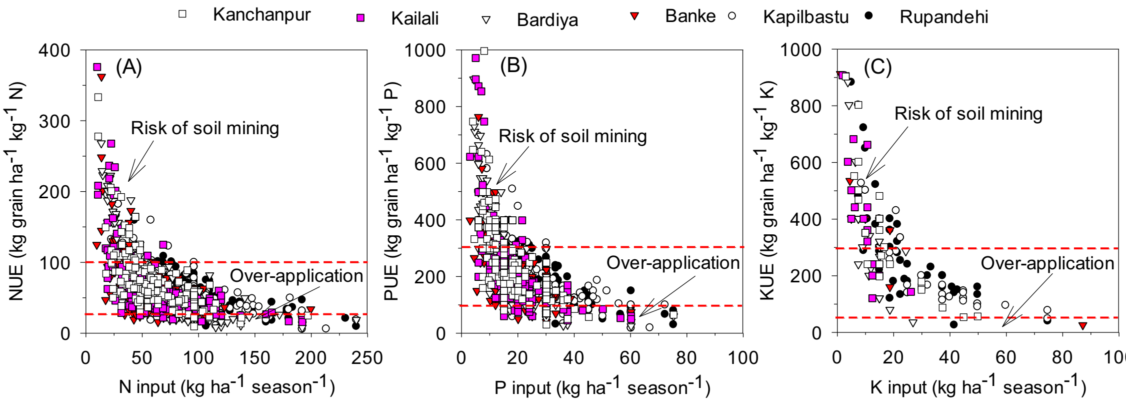

Fig. 3. Nitrogen- (A), phosphorus- (B) and potassium- (C) use efficiency in six surveyed districts. Above the horizontal lines indicate the range of possible risk of soil mining and below the below horizontal line over-application.

Table 4
Economic and environmental indicators of rice production in six Terai districts from household survey data 2016. Values are mean ± SD.

Input parameters	Kanchanpur	Kailali	Bardiya	Banke	Kapilbastu	Rupandehi
Economic indicators						
Total variable cost of production, US\$ ha^{-1}	579 ± 101	562 ± 61	602 ± 75	562 ± 67	620 ± 72	641 ± 75
Grain yield, t ha^{-1}	3.65 ± 1.24	3.33 ± 1.26	3.40 ± 1.26	3.23 ± 1.33	4.97 ± 1.54	4.92 ± 1.51
Gross margin, US\$ ha^{-1}	267 ± 276	210 ± 274	186 ± 283	188 ± 279	533 ± 337	500 ± 329
Environmental indicators						
Water productivity, kg grain m^{-3} water	0.283 ± 0.109	0.208 ± 0.079	0.220 ± 0.088	0.287 ± 0.120	0.346 ± 0.108	0.289 ± 0.091
Greenhouse gas emission intensity (GHGI), kg CO_2 equivalent t^{-1} yield	1053 ± 401	1187 ± 457	1203 ± 541	1243 ± 597	933 ± 586	930 ± 416
Nitrogen use efficiency (NUE), kg grain kg^{-1} elemental N	75 ± 43	69 ± 50	68 ± 57	72 ± 68	63 ± 35	57 ± 24
Phosphorus use efficiency (PUE), kg grain kg^{-1} elemental P	270 ± 176	236 ± 320	245 ± 196	289 ± 550	209 ± 126	187 ± 79
Potassium use efficiency (KUE), kg grain kg^{-1} elemental K	341 ± 224	510 ± 427	330 ± 229	743 ± 1146	322 ± 465	382 ± 427

(<20 kg ha^{-1}; 52%), and K (<15 kg ha^{-1}; 92%) (Fig. 3), resulting in high partial factor productivities. On the other hand, a small minority of farmers appear to be over-applying fertilizers with high rates or low efficiencies of N (>150 kg ha^{-1} or NUE <30; 18%), P (>30 kg ha^{-1} or PUE < 100; 11%), and K (>30 kg ha^{-1} or KUE < 50; 3%) infrequently observed. Mean water productivity was 0.27 kg grain m^{-3} when irrigation and rainfall were combined (total water productivity; 4428 L water kg^{-1} grain), and GHGI (CO_2 equivalent) was 1100 kg t^{-1} grain (Table 4).

3.1.4. Sustainability indicators as affected by supplemental irrigation, N rate, variety used, and land-holding (computed from household survey)

Excluding other causal factors, application of two supplemental irrigations with the additional cost of US\$ 88 ha^{-1} increased yield (1.0 t ha^{-1}), gross margin (US\$ 208), total water productivity (12%), and NUE (14%) while reducing GHGI by 23% (Fig. 4). Likewise, an increase in the N rate (calculated for the top and bottom halves of the distribution, i.e., ≥72 kg ha^{-1}) increased the averaged production cost by US\$ 70 ha^{-1} (@ USD 1.01 kg^{-1} elemental N) but increased yield (0.9 t ha^{-1}) and gross margin (US\$ 141 ha^{-1}). The use of hybrid rice increased the production cost by US\$ 47 ha^{-1}, but increased yield (0.7 t ha^{-1}), gross margin (US\$ 123 ha^{-1}), and water productivity (21%), while reducing GHGI by 7%. Our data also indicate that smallholder farmers (<0.44 ha rice area) have a higher cost of production (US\$ 15 ha^{-1}) but have a higher yield (0.3 t ha^{-1}), gross margin (US\$ 55 ha^{-1}), and water productivity by (11%), while decreasing GHG emission per kg grain (by 12%). The negative correlation (−0.43, $p = 0.10$) between rice plot area and yield indicates that smallholder farmers are achieving higher yield with better sustainability indicators compared to farmers with larger plot size, perhaps highlighting the importance of skilled and adequate labor as an enabling factor for sustainable intensification.

3.2. Determinants for rice yield gaps and their response to yield

3.2.1. Variability in yield determinants across districts

The RF model used to predict yield had a fairly high RMSE (1317 kg grain ha^{-1}) and somewhat modest R^2 (36%) (Fig. S6). The survey data analyzed using the RF model showed that the number of irrigation events was the most influential primary determinant for explaining variation in rice yield followed, in descending order of importance, by the occurrence of late-season rainfall, soil type, the occurrence of early-season rainfall, farmer perception of water stress, soil pH, and application of N and P fertilizers (Fig. 5). Model results suggest a difference in the relative importance of the variables explaining current grain yield variation across the districts (Fig. 6). Seedling age and FYM application rate were the top two important variables explaining yield in Kanchanpur. Similarly, N rate and SOC content in Kailali; the presence of water stress and soil type in Bardiya; irrigation intensity and the presence of water stress in Banke; the presence of water stress and land type in Kapilbastu; and land area and irrigation intensity were the top two major variables explaining rice yield in Rupandehi.

3.2.2. Response of grain yield to change in individual variables

Partial dependency plots (PDPs) were used to characterize univariate yield responses to different driving factors. Positive responses for grain yield were characterized until the following thresholds were reached: 5 irrigations, soil pH of 6.7, N rates of 110 kg ha^{-1}, P rate of 30–35 kg ha^{-1}, K rate of 20–30 kg ha^{-1}, transplanting date of July 1 to 20, and seedling age of 20–30 days (Fig. 7). The PDP for irrigation events suggests a 0.4 t ha^{-1} yield gain with single supplementary irrigation, increasing to 1.1 t ha^{-1} with diminishing returns for four supplementary irrigations (Fig. 7A). The PDP model suggests a positive response to the amount of late-season rainfall, where grain yield increased by 0.5 t ha^{-1} when rainfall amount during (2nd half of Sept) increased by 100 mm (from 200 mm to 300 mm) (Fig. 7B). Grain yield decreased by 0.25 t

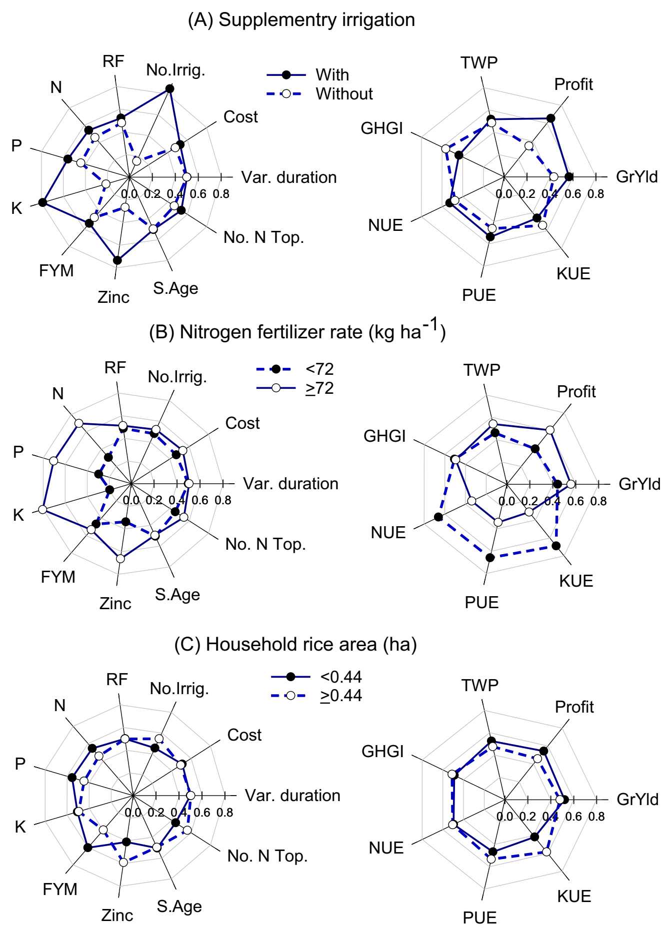

Fig. 4. Trade-offs in inputs (*left*) and indicators (*right*) between supplemental irrigation (with (≥1) irrigation) vs. without (no irrigation) (A), N application rate < 72 vs. ≥72 kg N ha^{-1} (below and above average) (B), and rice area < 0.44 vs. ≥0.4 ha (C) in the western Terai region. Fig. 2 for detail explanation of figure labels.

ha^{-1} when early-season rainfall increased by 100 mm (from 375 mm to 475 mm) (Fig. 7C). With respect to response to fertilizers, the PDP model suggests that grain yield increases by 5.6 kg ha^{-1} with each kg of N fertilizer application when N fertilizer rate increased from 50 to 100 kg N ha^{-1} (Fig. 7D), by 4 kg ha^{-1} with each kg of P fertilizer application when P fertilizer rate increased from 25 to 50 kg ha^{-1} (Fig. 7E), and by 10 kg ha^{-1} with each kg increased in K fertilizer when K rate increased from 20 to 40 kg ha^{-1} (Fig. 7F). For the other major yield determinants, the PDP model suggests positive responses to soil type (Fig. 8A), absence of water stress (Fig. 8B), soil pH, and transplanting time. Medium soil type out-yielded heavy and light-textured soils by 0.73 t ha^{-1} (18%) and rice without farmer-reported water stress had yield higher by 52% (1.6 t ha^{-1}) than with water stress (Fig. 8).

3.3. *Response of agronomic practices for closing the yield and profit gaps*

Our results from multiple experiments indicated that experimental treatments evaluated (Table 1) have considerable scope to increase rice yields, thereby closing YGs (Fig. 9). For example, transplanting earlier than July 10 increased yield by 0.55 t ha^{-1}, the use of healthy seedlings increased yield by 0.85 t ha^{-1}, and planting of hybrid cultivars by 1.1 t ha^{-1}, all independent of other changes in crop management. Integrated 'good agronomic practices' (GAP) increased yield by 48% (1.86 t ha^{-1}) and profitability by 94% (243 US$ ha^{-1}), where GAP had 5.74 t ha^{-1} yield and 500 US$ ha^{-1} profitability compared to prevailing farmer practices (FP2), i.e., 3.88 t ha^{-1} yield and 257 US$ ha^{-1} profitability (Fig. 10). Also, to understand the trend, the comparison of FP1 and FP2 showed yield by 14% (0.56 t ha^{-1}); and profitability by 50% (129 US$ ha^{-1}) were increased when farmers received training on GAP practices (FP1) compared to FP2. The paired compared 83 GAP vs. FP1 treatments showed 29% increment in yield (by 1.3 t ha^{-1} yield and 113 US$ ha^{-1} profitability with the GAP in the Terai region of Nepal.

4. Discussion

Food insecurity and an increased focus on profitability have motivated renewed attention to defining and describing YGs in the context of multi-functional agriculture (Laborte et al., 2012; Lobell et al., 2009; van Ittersum et al., 2013), including environmental sustainability Devkota et al., 2019b, 2020. In our study in the Terai of Nepal, diagnostic surveys, machine learning, and crop simulation characterized exploitable and total YGs of 2.58 and 4.85 t ha^{-1}, respectively. Rice YGs and their predictors vary across districts (Figs. 1, 5, and 6). In general, our analysis suggests synergies rather than trade-offs between closing YGs, increasing profitability, and reducing yield-scaled GHG emissions.

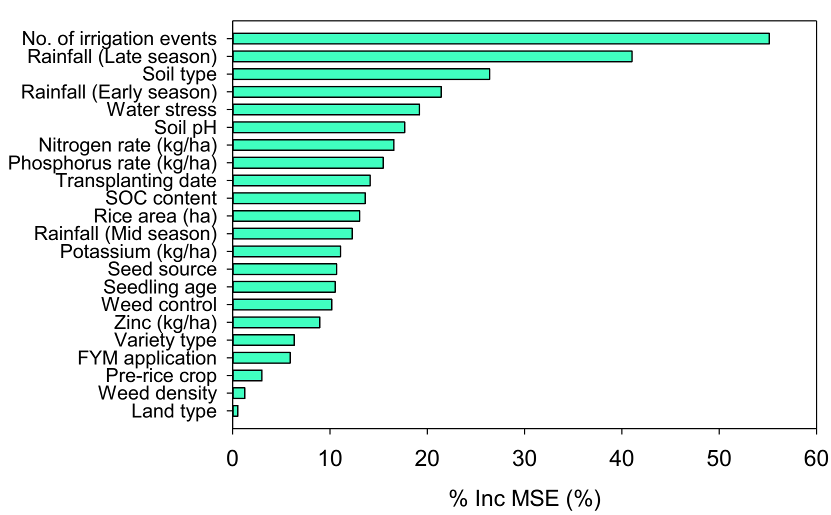

Fig. 5. Random forest results on relative importance of different variables (determinants) for explaining variation in rice yield in western plain region (overall of six districts) of Nepal.

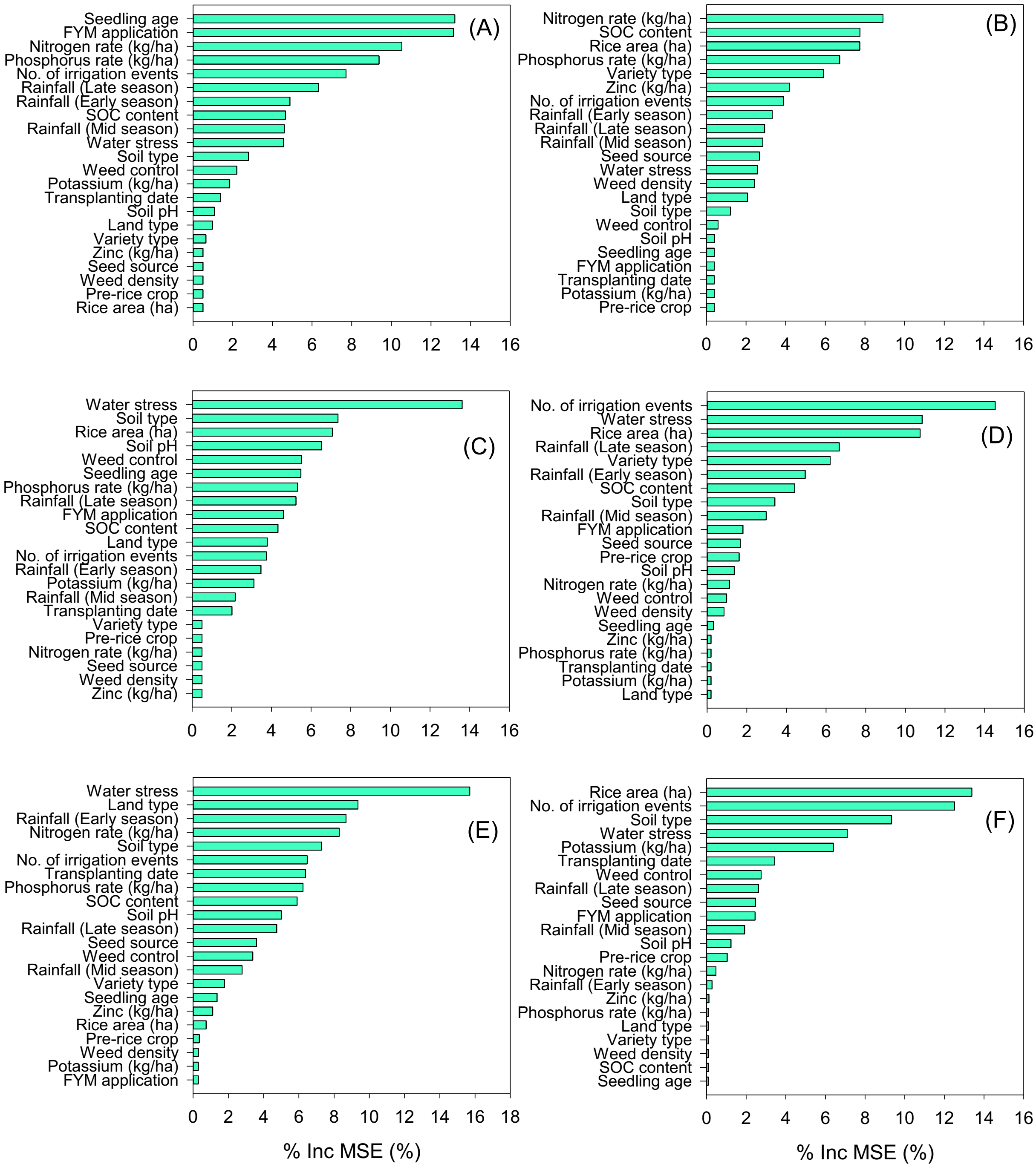

Fig. 6. Random forest results on relative importance of different variables (determinants) in explaining productivity drivers vary across districts, i.e., Kanchanpur (A), Kailali (B), Bardiya (C), Banke (D), Kapilbastu (E), and Rupandehi (F) of Nepal.

4.1. Optimization of production inputs and improvement of economic and environmental indicators

In the Nepal Terai, our results suggest that rice profitability is typically negative until yields exceed 2.1 t ha^{-1} (see Bottom 10% farmer in Table 3). Hence, rice production in this region is primarily for subsistence (average profitability US$ 1.4 ha^{-1} day^{-1} with 44% farmers producing <2 t ha^{-1}). As profitability is significantly correlated (r = 0.98) with yield, closing YG is the major entry point for increasing profitability and similar finding have been reported by Barbieri and Santos (2020).

Rice yield is positively correlated ($p < 0.001$) with the amounts of NPK fertilizers applied (Table 2 and Table 3), as result that is also reported by Devkota et al. (2019b, 2020) elsewhere in Asia. Our study also suggests that a significant number of farmers are likely 'mining' (i.e. removing more than is replenished) soil nutrients because very low rates of fertilizer are applied, e.g. 33% of surveyed farmers apply <50 kg N ha^{-1}, 52% apply <20 kg P ha^{-1}, and 92% <15 kg K ha^{-1} (Fig. 3). These studies clearly indicate that very high use efficiency is often associated with soil nutrient mining, where the optimal NUE, PUE, and KUE are 68, 385, and 69 kg grain kg^{-1} elemental N, P, and K respectively in rice (Dobermann, 2000). Low fertilizer application rates in Nepal are likely related to the high prices of informally traded fertilizers, delays in market availability, and investment aversion due to production risks (i.

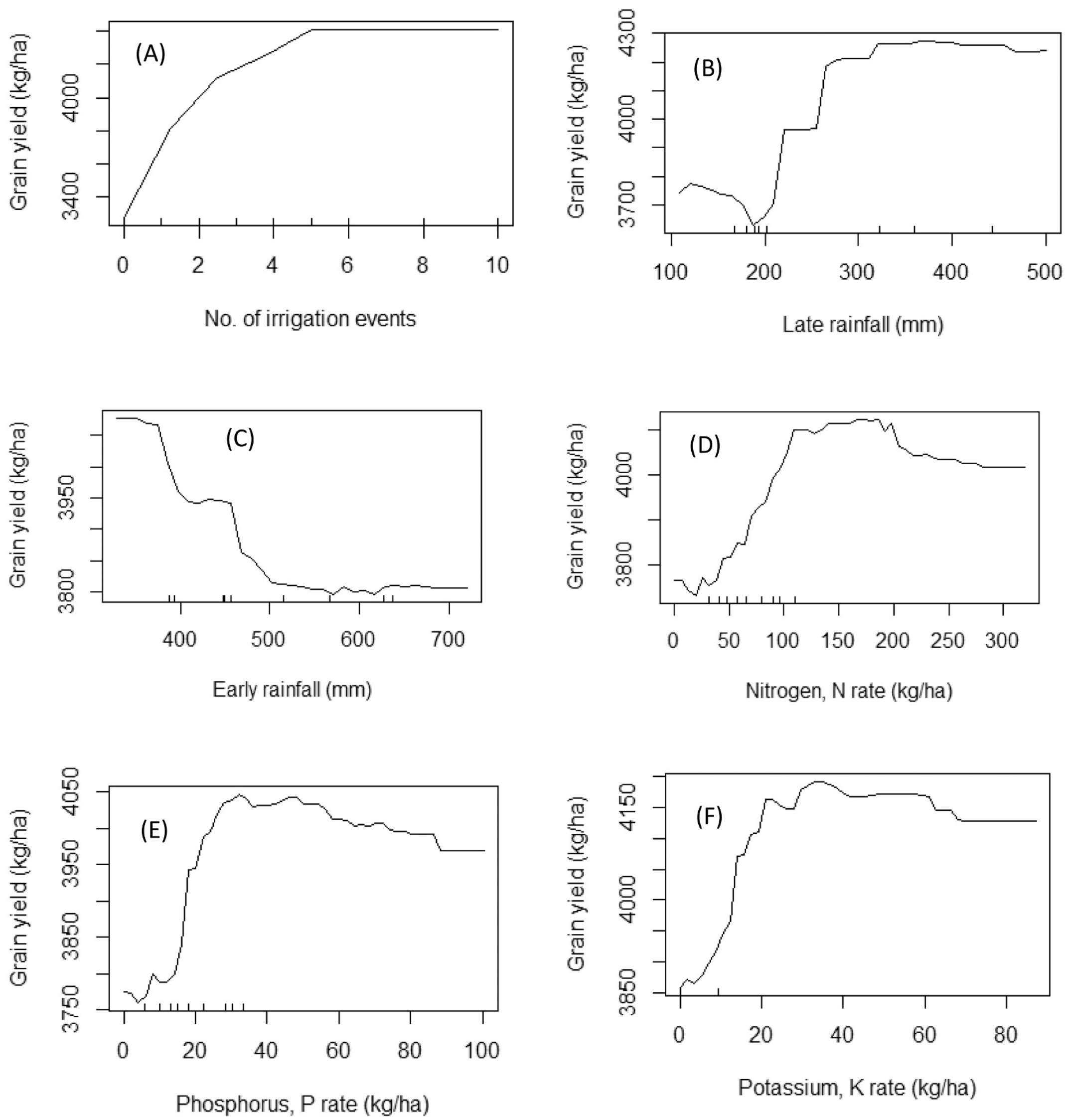

Fig. 7. Partial dependence plots (PDP) for the top-ranked predictor variables for grain yield from variable importance measures of Random Forest model: no. of irrigation events (A), late-season rainfall (B), early-season rainfall (C), nitrogen rate (D), phosphorus, P rate (E), and potassium, K rate (F).

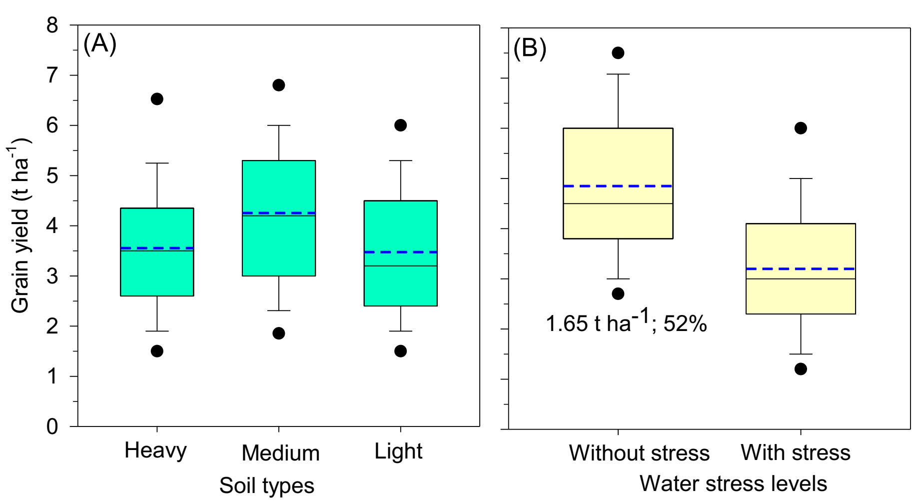

Fig. 8. Rice yield (t ha^{-1}) as affected by different soil types (A) and water stress levels (B). Black solid line median and the blue dotted line mean.

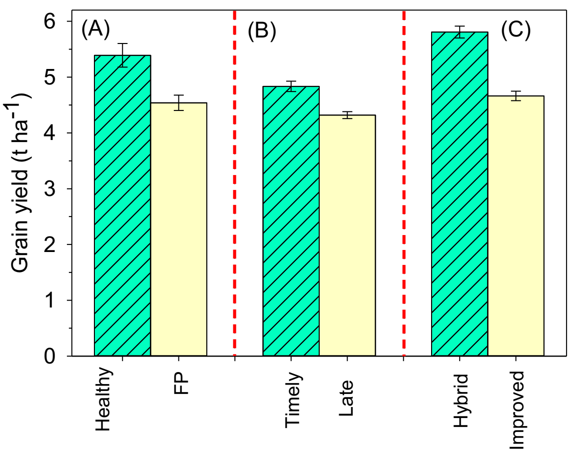

Fig. 9. Average effect of healthy vs. Farmers Practice (FP) seedling (A), transplanting time (timely vs. late) (B), and rice variety (Hybrid vs. Improved) (C) for closing the yield gap. Data from a series of on-farm experiments from 2011 to 2017 from eight districts and more than 30 sites. *Note: In this figure, three different experiments has been separated by vertical red dotted line for the better visualization.*

e. drought, flood). Our results suggest that the application of mineral fertilizer rates that exceed current average farmer practice (i.e. $\geq$ 72, $\geq$ 21, and $\geq$ 3 kg ha^{-1} elemental N, P, and K, respectively) will have wide-ranging benefits for yield, gross margin, and water productivity while reducing yield-scaled GHG emissions, especially given that current rates are well-below the response thresholds suggested by RF analysis of survey data through PDPs (see Fig. 7). Note that since very few farmers applied a high rate of fertilizer, the full range of fertilizer response values cannot be definitively defined through RF-based models derived from current survey data.

Setting baseline and the target is essential for the improvement of sustainability indicators in each district and agro-ecological region. This study has proposed a baseline (the population mean) and the target (the value of top 10%) for seven economic and environmental indicators of rice production for the Terai region (Table 3). Application of targeted site-specific science-based recommendations (Figs. 7-10) including fertilizer and other crop management practices addressing the site-specific drivers (Fig. 6) is required to achieve sustainability goals over time. Also, these baseline and target values can inform planning processes for sustainable development (Bell and Morse, 2012).

4.2. *Determinants for grain yield variability*

In Nepal, current agronomic recommendations are extremely general and mostly address soil fertility management at the scale of broad geographic domains (i.e. fertilizer rate recommendations for irrigated and rainfed production in the Terai, hill, and mountain ecologies) (GoN, 2019). Our analysis on YG demonstrates the limits of such an approach by highlighting how determinants vary across Terai districts (Fig. 6), suggesting the need for location-specific interventions. For example, increasing N, P, and K fertilizers rates can substantially improve productivity and sustainability indicators in the Kanchanpur District, whereas Banke, Bardiya, and Kapilbastu Districts are comparatively water-stressed and integrated water resources management must be given the highest priority. In aggregate, our analysis suggests that the major drivers of yield variation are mostly related to irrigation or water supply (number of irrigation events, amount of rainfall during late and early crop season, farmer-perceived crop water stress). Accordingly, 72% of farmers (with the highest 88% in Banke and the lowest 41% in Rupandehi) reported the appearance of drought stress during the rice-growing season, a major factor constraining rice productivity. Also, 23% of farmers do not have access to irrigation and, among those that do have access, more than two-thirds irrigate 2 times or less. Reasons for low irrigation intensity are likely diverse and may include unreliable water supply, insufficient credit and labor availability, a lack of perceived benefits from irrigation, or investment aversion in the hope that rains may eventually come.

Total seasonal rainfall in the survey year of 2016 was 1382 mm, close to the long-term mean but unevenly distributed across the season. Availability of supplementary irrigation through groundwater and surface irrigation is increasing (CBS, 2019; Urfels and Mcdonald, 2020) and the Nepal government also has priority projects to increase irrigated area (Khanal et al., 2020), but clearly, there is more progress to be made. With an observed trend towards the early recession of monsoon rain (DHM, 2018), the use of shorter-duration rice cultivars could reduce production risks under water-limited conditions. Similarly, to adequately cope with early-season patterns of excess and deficit, early drought and submergence tolerant (*Sub-1*) cultivars are useful (Mackill et al., 2012; Singh et al., 2011). Decreased rice yield with more than 400 mm rainfall during the early growing season (Fig. 7C) could be associated with damage to young seedlings due to flooding. The positive correlation between grain yield and the amount of late-season rainfall indicated the scarcity of irrigation or late-season rainfall lowed yield mainly by delaying flowering, poor grain filling, and increasing spikelet sterility. Our analyses of survey data suggest that increased levels of supplemental irrigation ($\geq$2 irrigation events) lead to higher yields with lower GHGI and yield stability across years. Under the current condition

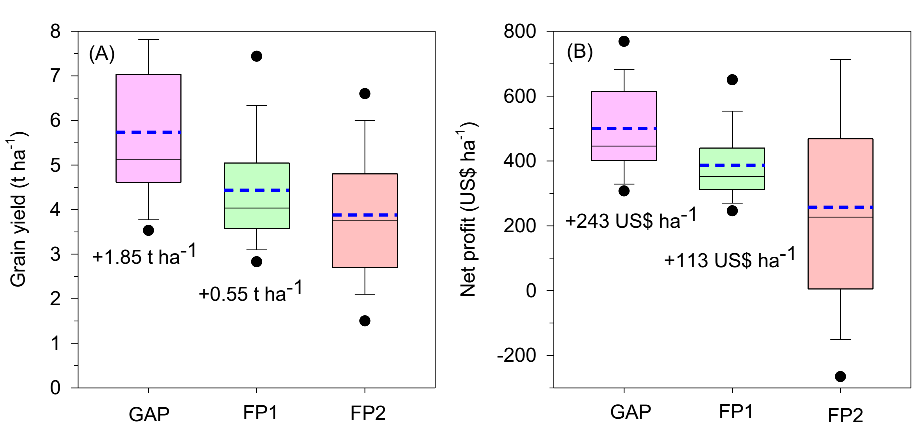

Fig. 10. Yield (A) and gross margin (B) under good agronomic practices (GAP) and farmers practice (FP) in 83 farmers field in western Terai plain (Experiment IV). GAP and FP1 were compared in paired on-farm experiment in 2017, FP2 is from the survey data. Note: FP2 are put together in this plot only for the better visualization and comparison between FPs. Black solid line median and the blue dotted line mean.

of rainfall variability, the yield and profit penalty and risk that farmers have to bear without supplemental irrigation is significant (see Fig. 4). With the investment of US$ 88 ha^{-1} in two irrigation, a more than two-fold increase in profitability was characterized in 2016 (Fig. 4).

Soil pH is another major causal factor for the yield variability as determined by machine learning analytics. Soil acidity has been considered a major constraint in Terai region and the government has put a major effort in PMAMP Project for managing soil acidity (MoALD, 2020). Together with soil acidity, the P rate tends to be the major yield predictor in a few districts, as P is commonly bound in insoluble forms in acidic soil (Ch'ng et al., 2014). Similarly, in Kapilbastu and Rupandehi, soil type is a major predictor of yield outcomes with medium-textured soil out-yielding heavier clay and sandy soils, a result consistent with others from the region (Prihar et al., 1985).

4.3. Potential of agronomic innovations for closing rice yield gap

In several rice-producing countries, the standards of 'good agronomic practices' (GAPs), have been formalized for example VietGAP and 1M5R in Vietnam, ThaiGAP in Thailand, three control (3CT; reduction in N input, plant density, and pesticide) program in China, integrated crop management (ICM) in Indonesia, best-management practices (BMP) in Myanmar (Devkota et al., 2019b; Stuart et al., 2018). This study has aggregated evidence from a variety of analytical methods to identify geographically differentiated entry points for sustainably closing the rice YG in Nepal. With various degrees of importance and geographic relevance, rice GAPs in Nepal rest on six component technologies: healthy seedlings, use of high-yielding hybrid or modern rice varieties, timely planting, recommended fertilizer rates, supplemental irrigation, and timely weed management.

5. Conclusions

By deploying a mixed-methods approach that combines observational studies with on-farm experiments and crop simulation, our analysis demonstrates that transformative increases in grain yield and profitability are possible in the rice systems of Nepal without jeopardizing key environmental sustainability indicators. Nevertheless, the significant biophysical, crop management, and socio-economic diversity in the agricultural systems of Nepal suggest that simply focusing on generalized packages of 'good agronomic practices' will not adequately support sustainable intensification. While formalization of GAPs as general guidance to farmers to support agricultural transformation, it is important to emphasize that productivity drivers vary by geography. By combing general principles for deriving yield gap, determining their determinants, and benchmarking baseline and target for the economic and environmental sustainability indicators, rice farmers in Nepal will be better placed to enhance yield, profitability, and environmental performance of their cropping systems.

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 work was supported by the Cereal Systems Initiative for South Asia (CSISA), an ecoregional project that is funded by the U.S. Agency for International Development (USAID) (Grant no. BFS-G-11-00002) in Nepal. The authors own a debt of gratitude for the exceptional technical staff from the International Maize and Wheat Improvement Center (CIMMYT) and International Rice Research Institute (IRRI) who along with collaborating farmers, farmers groups and research partners from the Nepal Agricultural Research Council (NARC) made this work possible. Comments and suggestions from three anonymous reviewers and the editor substantially improved the clarity and the quality of this manuscript.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.agsy.2021.103182.

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