Agricultural Systems 213 (2024) 103804

Contents lists available at ScienceDirect

Agricultural Systems

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

Opportunities to close wheat yield gaps in Nepal's Terai: Insights from field surveys, on-farm experiments, and simulation modeling

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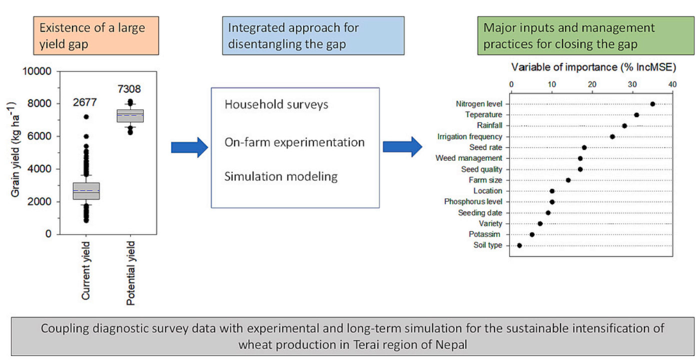
HIGHLIGHTS

- Low productivity & profitability typify wheat production systems in Nepal Terai
- Field survey, experiments & modeling were used to explore intensification options
- Yield gap of 1.6 t ha^{-1} & profit gap of 348 USD ha^{-1} exists in in wheat Nepal Terai
- Nitrogen, terminal heat & irrigation are principal drivers on yield & profit gaps
- Integrated good agronomic practices is required for closing yield & profit gaps

GRAPHICAL ABSTRACT



ARTICLE INFO

Editor: Dr. Jagadish Timsina

Keywords:
Good agronomic practices
Meta-analysis
Sustainable intensification
APSIM Next Generation
Random Forest
Genotype x Environment x Management

ABSTRACT

CONTEXT: Wheat (*Triticum aestivum*) is among the most important staple food crops in the lowland Terai region of Nepal. However, national production has not matched the increasing demand. From a South Asian regional perspective, average productivity is low with high spatial and temporal variability.
OBJECTIVES: This study determines entry points for closing yield gaps using multiple diagnostic approaches, i.e., field surveys, on-farm experiments, and simulation models across different wheat production environments in the Terai region of Nepal.
METHODOLOGY: Yield and production practice data were collected from 1745 wheat farmers' fields and analysed in tandem with over 100 on-farm experiments. These were complemented by long-term simulation modeling using the APSIM Next Generation to assess system production behavior over a range of climate years.
RESULTS AND DISCUSSION: On-farm survey data suggests that yield and profit gaps under farmers' management (difference between the most productive (top 10th decile) and average wheat fields) were 1.60 t ha^{-1} and 348 USD ha^{-1} in the Terai region. The potential yield gap (difference between simulated potential yield and surveyed population mean) estimated was 4.63 t ha^{-1}, suggesting ample room for growth even for the highest-yielding

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https://doi.org/10.1016/j.agsy.2023.103804
Received 1 February 2023; Received in revised form 1 November 2023; Accepted 2 November 2023
Available online 15 November 2023

fields. Machine learning diagnostics of survey data, and on-farm trials identified nitrogen rate, irrigation management, terminal heat stress, use of improved varieties, seeding date, seeding method, and seeding rate as the principal agronomic drivers of wheat yield. While fields in the top 10th decile yield distribution had higher fertilizer use efficiencies and irrigation and seeding rates with similar overall production costs as average-yielding farmers. Our results suggest a complementary set of agronomic interventions to increase wheat productivity among lower-yielding farms in the Terai including advancing the time of seeding by 7–10 days on average, increasing nitrogen fertilizer by 20 kg ha^{-1}, and alleviating water stress by applying two additional irrigations.

SIGNIFICANCE: Although wheat yields in the Terai are among the lowest in the region, biophysical production potential is high and remains largely untapped due to sub-optimal agronomic management practices rather than intrinsic agroecological factors. Data from this study suggests that incremental changes in these practices may result in substantial gains in productivity and profitability.

1. Introduction

Wheat is the second most widely cultivated staple food after rice in the lowland Terai ('plain') region of Nepal. It is grown on 0.71 million hectare with a total production of 2.2 million metric tons, primarily in sequence following rice during the cool winter period. In the country, wheat production accounts for 2.3% of the national gross domestic product (MoF, 2021), while compared to its productivity in India (3.46 t ha^{-1}), the average yield is consistently low (3.0 t ha^{-1}) (FAOSTAT, 2023). To meet domestic demand, the country imported 0.26 million tons of wheat in 2021, worth approximately USD 69 million, and with growing population growth and dietary changes, demand for wheat is projected to increase in the coming years. As a consequence, average national productivity must increase to 3.9 t ha^{-1} by 2030 to meet growing demand through domestic production (Devkota et al., 2022). As such, science-led knowledge-based efforts are needed to narrow the yield gap (YG) to reduce the increasing rate of import while potentially improving farm profitability.

Benchmarking yield and profit gaps and understanding the major drivers causing yield gaps are important to prioritize supportive policies and appropriate interventions for sustainable crop production intensification (Devkota et al., 2021; Lobell et al., 2009; van Ittersum et al., 2013; Stuart et al., 2016). Previous studies conducted on research stations under controlled conditions identified seeding time, fertilizer, water management, and terminal heat stress as major factors affecting wheat productivity in Nepal Krupnik et al., 2021). On-farm experiments suggest that terminal heat stress during grain filling poses a major constraint to wheat production in the region, with each day delays in wheat seeding after mid-November reducing wheat yield by approximately 50 kg ha^{-1} d^{-1} by shifting the crop maturation period into the late spring period when temperatures spike (Devkota et al., 2019a, 2019b; Giri, 1998; McDonald et al., 2022). In Nepal, wheat is also primarily cultivated with low input levels, highlighting opportunities for rational input use, which may benefit production and profitability (Park et al., 2018). A nutrient-limited attainable yield gap of 1.9 t ha^{-1} exists in Nawalparasi (one of the Terai districts) of Nepal (Devkota et al., 2018). Their data suggest that wheat yield can be increased by 95–184% through good agronomic practices such as good variety, no-tillage practice, timely seeding and weed management, balanced fertility, and irrigation water management. The selection of appropriate varieties for different seeding dates and input management practices has also been identified as crucial for closing the yield gap (Devkota et al., 2019a, 2019b). In addition to agronomic practices, productivity under farmers' management practices is affected by site factors including soil type, drainage class, and indigenous soil fertility. Therefore, it is important to determine why crops in some farmers' fields are not performing equally in other fields within a similar production environment as a first step towards identifying the major determinants and opportunities for improvement.

On-farm experiments, which can help bridge the gap between research and real-world farming conditions, offer opportunities to assess the context-specific value of novel agronomic interventions (Joshi et al., 2012). To complement the logistical and financial constraints associated with conducting on-farm experiments at scale, yield and production practice surveys can be combined with new analytical methods to determine current drivers of yield variation among fields and between regions. Machine learning approaches such as Random Forest (RF) models have been used for understanding yield gaps in rice and to identify optimal fertilizer rates, strategies for increasing nutrient-use efficiency, and reducing greenhouse gas emissions (Devkota et al., 2021; Timsina et al., 2022). Similarly, the dynamic simulation modeling approaches can also provide a useful complement to broaden the inference space beyond the climate years captured in experimental and survey data (Devkota et al., 2022; Holzworth et al., 2014; Keating et al., 2003).

The Agricultural Production Systems sIMulator (APSIM) cropping systems simulation model simulates wheat growth, development, and yield as affected by climate, soil, water, and nitrogen management practices (Holzworth et al., 2014; Devkota et al., 2023). APSIM has been used to simulate the effect of irrigation and nitrogen (N) rate in the Indo-Gangetic Plains of South Asia (Chaki et al., 2022). It has also been applied to seeding date and irrigation management in Punjab, India (Balwinder-Singh et al., 2016), and interactions between cultivar, environmental and management parameters from a global wheat dataset (Zhao et al., 2014). It has been extensively evaluated using experimental data and is deemed capable of accurately predicting yield variability caused by rainfall and different management practices (Gaydon et al., 2017).

In many circumstances, coupling diagnostic survey data with experimental and long-term simulation approaches may be needed to identify pathways for improving the sustainable intensification of crop production. This study builds in response to prior work by Park et al. (2018) in Eastern Indo- Gangetic Plain that focused on diagnostic on-farm surveys in 1181 households including a few parts of the Terai region of Nepal and Bihar, India. However, that study did not incorporate insights from dynamic simulation and on-farm trials. This research provides additional emphasis on the Western Terai which constitutes a focal region for the Government of Nepal and international donors for sustainable agricultural development and enhancing food security by reducing wheat imports. Thus, the objectives of this study were to determine drivers of wheat yield and productivity outcomes in the Nepal Terai and to understand the role of genotype × environment × management practices in defining pathways to sustainably close yield gaps in wheat production for the Terai region of Nepal.

2. Materials and methods

The study includes data from three sources: (1) on-farm surveys conducted in seven Western Terai districts in the 2016/17 wheat growing season, (2) three years (2015–2017) of on-farm experiments conducted in the same Western Terai districts, and (3) long-term crop simulations driven by daily weather data from 1984 to 2021 using NASA Power data (NASA POWER 2021) in nine different Terai districts (Fig. 1).

2.1. Study sites

Survey and on-farm experimental data were collected in project districts of the Cereal Systems Initiatives for South Asia (CSISA; https://csisa.org) (Fig. 1A). Study sites have a humid climate with a wet season (May through September) and dry season (October through April). Long-term (1987–2017) average total annual rainfall was 1566 mm, with 89% of the mean total rainfall occurring during the rainy season (May to September), the average annual maximum temperature 30.6 °C, the minimum temperature 18.8 °C, and the mean solar radiation 15.8 M J m^{-2} d^{-1} (Fig. 1B).

2.2. Household surveys

2.2.1. Characterization of wheat production under farmers' management

Wheat production practices were characterized through household surveys (N = 1745) in seven western Terai districts, i.e., Rupandehi, Kapilvastu, Dang, Banke, Bardiya, Kailali, and Kanchanpur in 2017 (Fig. 1A). To ensure a representative range of crop management and yield variation outcomes, a purposive sampling scheme was employed using remote sensing-based enhanced vegetative index (EVI) values derived from Landsat images at a spatial resolution of 30 m × 30 m. The detail of the similar sampling methodology is described in (Paudel et al., 2017) and Devkota et al. (2021). In each district, images were analysed from mid-February to the first week of March 2017, reflecting the period when wheat reaches maximum EVI. The value of EVI in each district was normally distributed. To capture samples proportionally to the distribution of the district, the mean, standard deviation, minimum and maximum values of EVI were computed. Sampling locations for each district were selected based on a probability proportionate method given the visible normal distribution of EVI. The gridded EVI values were first stratified into six quartiles and samples were drawn randomly from each quartile. Using this approach, a total of 1745 production plots were selected (i.e., 80, 80, 40, 40, 5, and 5 from two sides of the distributional curve, i.e., mean EVI ±1 Standard Deviation (SD), mean ± 2 SD, and mean ± 3 SD) from each district.

Surveys were deployed for the largest production field for each farmer respondent using Open Data Kit (ODK; https://getodk.org/) using a structured questionnaire with fields geotagged. We used a self-reporting methodology for yield assessment to overcome logistical bottlenecks posed by physical crop-cuts. Results from previous surveys in rice (Devkota et al., 2021) demonstrate the close correspondence

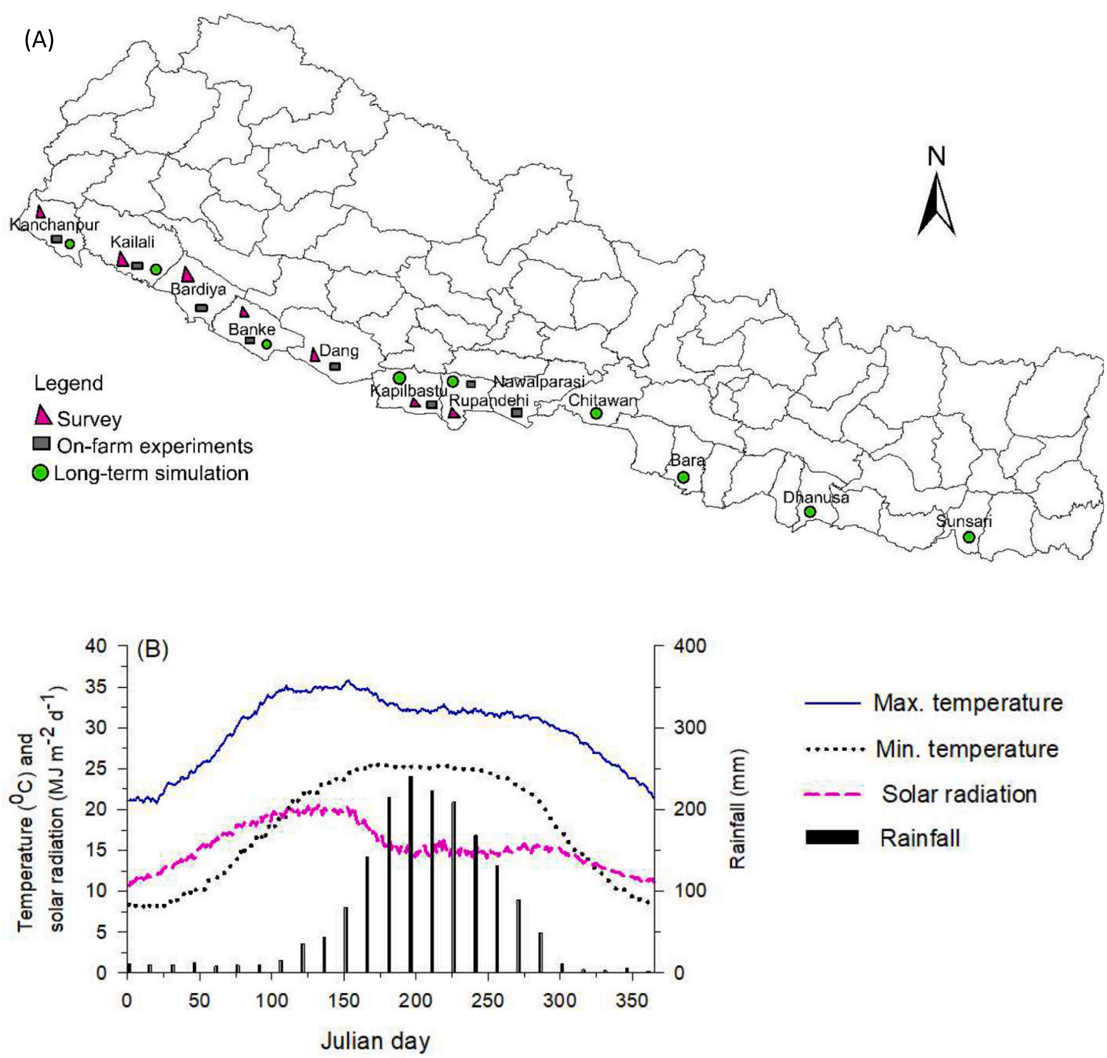

Fig. 1. Map showing study sites (survey, on-farm experimental sites, and long-term simulation) (A) and daily maximum and minimum air temperature (°C), solar radiation (MJ m^{-2} d^{-1}), and half-monthly (15 days) total rainfall (mm) from the averaged of seven western Terai districts from long-term data from 1987 to 2017 (B). Maximum temperature, minimum temperature, and rainfall were the measured data and the solar radiation was taken from the NASA Power Project data (NASA POWER, 2023).

between farmer reported yield and the crop-cut based yield assessments in Nepal (Fig. SI1). Production practice information such as the timing of all major field operations, seeding time, the variety planted, the amount and timing of organic and inorganic fertilizer and herbicide utilized, the number of irrigation events, insect pests, diseases, and other weed control measures were recorded. A full description of the survey instrument is described in Paudel and McDonald (2021).

2.2.2. Computation of input and efficiency indicators and yield and profit gaps

Crop production parameters (mentioned above) were surveyed for the largest plot (selected largest wheat field if farmers have many scattered field parcels in different areas) and converted to a per-hectare rate. From the largest plot, grain and straw yields were calculated from farmers' reported yields based on sun-dried weight. As the questionnaire elucidated partial budgets only, we computed total production cost from the input (seed, fertilizer, irrigation, weed management) rates reported by individual farmers supplemented with additional information, e.g., machinery cost for land preparation, crop establishment, and threshing. The labor used for wheat production was collected from a follow-up survey with five randomly selected farmers in each studied village, with the average value for each village used. Production cost also includes the imputed value of family labor but excludes fixed and sunk costs (e.g., land charge, cost of machinery purchases, etc.). In summary, total production costs were calculated from inputs (seed, fertilizers, irrigation, herbicide) and all labor and machinery used (land preparation, crop establishment, harvesting, threshing, drying, and cleaning). Total income was computed considering a per kg grain price of USD 0.23 (the government price validated with the market price in the study year and average exchange rate of USD 1 = 103 Nepalese rupees). A straw price of USD 0.014 per kg was also applied (local market price of study year). Net profit was computed by subtracting total production cost from total income (including grain and straw). Nitrogen use efficiency (NUE) and phosphorus use efficiency (PUE) were calculated as partial factor productivities (kg grain per kg nutrient element) of nitrogen and phosphorus by dividing the reported grain yield by the amount of the respective nutrient applied (Ladha et al., 2005).

To compute grain yield and net profit gaps, fields were first classified into three categories, including the top 10th decile, the majority (between 2nd and 9th deciles), and the lowest performing 1st decile fields. Then we applied the method described by Devkota and Yigezu (2020), where the current productivity gap between high and low-yielding fields was computed as the difference between the mean yield of the top (10th) decile and the mean yield of all other farmers not in the top decile (i.e., 1st-9th deciles).

2.2.3. Machine learning analytics

Random Forest (RF) is an ensemble tree-based method for classification or regression (i.e., binary or continuous dependent variables) that avoids model overfitting and improves the accuracy of prediction by using bagging (i.e., data record sub-setting) and a random set of features (i.e., predictor variables) to generate a 'forest' of predictions (Breiman, 2001; Breiman and Cutler, 2012). Classification and regression tree (CART) constructs a single prediction model rather than an ensemble. Although the predictive power of CART is generally lower than RF, CART results are readily interpretable and the two approaches can be used synergistically (Breiman, 2017). In this paper, we applied RF and CART models to analyze the major determinants of variations in yield and net profit for the survey data from the western Terai region of Nepal through the variable of importance and partial dependence plots (PDPs).

We used the 'randomForest' and "party" packages (Hothorn et al., 2015) of the statistical program R for RF and CART analysis while also following Liaw and Wiener (2002) to set the parameter values for model estimation. Models were trained using 80% of the data, with 20% reserved for independent model verification. Eighteen different yield predictor variables, i.e., location, land holding size, soil type (light, medium and heavy texture), the input used (seed, fertilizer, irrigation events), seeding time, seeding method, severity during the wheat growing period (mostly early crop growth stage), weed management, amount of seasonal rainfall, and temperature at flowering and grain filling, were used in RF and CART analysis of grain yield.

2.3. On-farm experiments

To verify insights from farmers' field survey data and to test technologies that were not well-represented among farmer practices, 102 on-farm experiments (Table 1) were implemented across eight Terai districts (Banke, Bardiya, Kailali, Kanchanpur, Nawalparasi, Rupandehi, Dang, and Kapilbastu) over a three-year period (2014–2017). Four different experiments were conducted with farmers' fields treated as experimental replicates including, (1) seeding date × nitrogen rate, (2) irrigation rate × nitrogen rate, (3) irrigation rate, and (4) precision application of nitrogen fertilizer (Table 1). Participating farmers were selected to be representative of the spatial heterogeneity existing in the village or the landscape and based on their willingness to manage plots according to the researcher designed experimental protocols. All the measurements were collected by researchers as per the research protocol.

Across locations, individual experimental field sizes ranged from 250 to 300 m^2. All fields were under rice-wheat rotation with farmers planting rice with their own management practices prior to the initiation of wheat experiments. In each experiment, a farmer practice (FP) control plot was grown in an adjacent field to the experimental plots with farmers using their own management practices which were recorded. In all experiments, the wheat crop was planted at 20 cm line spacings by machine. Unless specified as treatment in Table 1. Wheat was planted between 10-30th November with 2–3 irrigations (i.e., at crown root initiation, flowering, and grain filling) with the crop harvested by the end of April. In all plots, 40 kg P_2O_5 and 25 kg K_2O ha^{-1} were applied basally before seeding. Weed management was carried out through one application of Leader (Sulfosulfuran 75% WG) at 33.75 g a.i. ha^{-1} when weeds were 3–4 leaf stage. Wheat was harvested from three 4 m^2 locations (top, middle, and bottom) within fields and bulked to obtain the total harvested area of 12 m^2. Grain yield was reported at 13% moisture content.

2.3.1. Simulation for long-term performance assessment of seeding date, irrigation, and fertilizer management practices

Input data: Soil properties for two dominant soil types (sandy loam, clay loam) of the Terai region of Nepal that were used to parameterize the APSIM Next Generation (APSIM NG) model are described in Table SI1. Root biomass of 700 kg ha^{-1} and C:N ratio of 100 (g g^{-1}) of previous rice straw, crop sown actual seeding date (differ across districts), seeding depth of 30 mm, row spacing of 250 mm, plant population at seeding of 120 were used for model calibration under initial conditions. To assess yield potential in the absence of agronomic constraints, automated irrigation levels and 200 kg N ha^{-1} were simulated. Crop management-specific parameters, such as planting date, emergence date, planting method, density, seeding depth, row spacing, fertilizer types, rates, application dates, irrigation depth and date, and harvesting dates were recorded for each plot during the experimental period at all locations and years and were used during model calibration and performance verification. Daily weather data from 1984 to 2021 required for the model, e.g., rainfall, minimum and maximum air temperature, solar radiation, relative humidity, and wind speed, were derived from the NASA Power Project (NASA POWER, 2021) for four environments (one environment each district, i.e., Kailali, Banke, Bardiya, and Rupandehi). As NASA Power is a 0.5 × 0.5 degree gridded climate product and may need local adjustments, we compared it with measured maximum and minimum temperatures and solar radiation from 1984 to 2000 in Banke (Fig. SI2). Based on this analysis, climate data were adjusted by decreasing solar radiation by −12%, maximum

Table 1
Details of on-farm experiments conducted during wheat growing season in different Terai districts during 2014–2017.

Experiment number	Experiment name	Total no. of experiments	Total No. of treatments	Year (all 2 Years)	District	Seeding date	Fertilizer (N: P_2O_5:K_2O) rate (kg ha^{-1})	No. of irrigation	Variety
I	Seeding date × N rates	49	8	2016–2017	Kailali, Banke, Bardiya,	Timely: 10–30 November Late: 1–20 December	60:40:25 (FP) 100:40:25 120:40:25 125:40:25 150:40:25 150:50:50	Common irrigation at CRI, flowering, and grain filling	Vijay, Bhrikuti, Gautam, Aditya
II	No. of irrigation × N rates	18	9	2014–2015	Banke, Bardiya, Kailali	20–25 November	60:40:25 (FP) 100:40:25 150:40:25	1, 2, and 3-times irrigation	Vijay, Bhrikuti
III	No. of irrigation	10	3	2015–2016	Kanchanpuur, Kailali, Banke, Bardiya, Rupandehi	20–25 November	100:40:25	2, 3, and 4-times irrigation	Vijay, Bhrikuti
IV	Precision N application (Precision spreader vs. Farmers FP)	25	2	2015–2016	Kanchanpur, Banke, Bardiya	20–25 November	100:40:25. Use of precision spreader	Irrigation at CRI, flowering, and grain filling	Gautam

temperature by −1.14 °C, and minimum temperature by −1.93 °C. Similarly, for scenario analysis, model was run under nine environments (districts). The wheat variety Bijaya (released in 2011 for the Terai and lower valley regions up to 500 masl, 111–123 days maturity and attainable yield of >6.5 t ha^{-1}) (NARC, 2014) was calibrated and validated for six environments, i.e., Kanchanpur, Kailali, Bardiya, Banke, Rupandehi and Nawalparasi.

Model calibration and verification: The model was calibrated using crop growth data from an on-farm seeding date × N rate experiment (Experiment I, Table 1). Model performance was verified using an independent dataset from a separate on-farm trial conducted during the same period where both irrigation and nitrogen rates varied (Experiment II, Table 1). Model outputs were assessed based on the mean, the ratio between simulated and measured, standard deviation, the coefficient of determination (R^2), absolute root mean square errors (RMSEa), and normalized root-mean-square errors (RMSEn, %) for days to anthesis, days to maturity, and grain yield. We considered the model to reproduce experimental data best when the ratio between simulated and measured R^2 were close to 1.0 (Timsina and Humphreys, 2006; Yang et al., 2014).

Eqs. 1–3 were used for model performance assessment as follows:

$$RMSE_a = \left(\frac{1}{n}\sum (Y_i - X_i)^2\right)0.5 \tag{1}$$

$$\mathrm{RMSE_n}(\%) = 100 \times \frac{\left(\left(\frac{1}{n}\right)\sum(Y_i - X_i)2\right)0.5}{\sum Xi/n} \tag{2}$$

$$d = 1 - \frac{\sum_{i=1}^{n}(Yi - Xi)^2}{\sum_{i=1}^{n}\left(\left|Y_i'\right| + \left|X_i'\right|\right)^2} \tag{3}$$

where, Y_i and X_i are simulated and measured values, respectively, X_i is the mean of all measured values, d refers to d-stat, and *n* is the number of measurements.

2.3.2. Long-term simulations

APSIM Next Generation was used to characterize yield potential for different seeding dates, N fertilizer rate, irrigation management, and their interaction across selected sites/districts. Unless noted, all scenarios applied the same variety and crop management practices. Soil data required for APSIM NG were obtained from ISRIC (Batjes, 2012) and applied to each site/district.

Potential yield is the crop yield grown under optimal management practices (i.e., recommended plant density, non-limiting nutrient condition, effective control of biotic stresses, etc.) in farmers' fields (Van Ittersum et al., 2013). In this study, model was run to quantify potential yield (biophysical yield potential) for nine Terai districts under non-limiting water (i.e., turning on the 'automatic irrigation' routine one week before seeding to before crop harvest, i.e., 30th of March, allocation of sufficient season water (1000 mm), re-irrigation to 100% plant available water content (PAWC) when it drops to 95%, for each day of simulation if required, and a maximum irrigation application rate of 50 mm d^{-1}). The model also included non-limiting nutrient conditions (200 kg N ha^{-1}; 50 kg basal, and the remaining at equal 3 splits) for eight seeding dates starting from 15 September to 01 January at 15 days intervals in nine different districts/sites (Kanchanpur, Kailali, Banke, Kapilbastu, Rupandehi, Chitwan, Bara, Dhanusha, Sunsari). To explore the potential for closing wheat yield gaps with supplementary irrigation, we compared five irrigation scheduling methods, i.e., rainfed and irrigation applied at 25%, 50%, 75% and 95% PAWC) using APSIM NG for each district, fertilizer rates, and seeding dates combination. In the 1st three, i.e., 25%, 50%, 75% PAWC irrigation stopped when 90% of the PAWC was reached, while in 95% PAWC, irrigated when it dropped to 95% and irrigated up to 100% PAWC. To optimize the N rate as affected by irrigation, district/site, seeding date, five levels of N rates (0, 50, 100, 150, and 200 kg N ha^{-1}) were run for long-term under nine districts/sites (Fig. 1), five water management (above), and eight seeding dates.

2.4. Statistical analysis

Yield gaps under farmers' management (YG-FM) were derived for six surveyed Terai districts. Based on yield from the household survey farmers were categorized into three categories and an overall yield gap under farmers' management' was computed as the difference between the mean yield of the top (10th) decile and the mean yield of all other farmers who are not in the top decile (i.e., 1st − 9th deciles) divided by the mean of top 10th expressing as a percentage. Potential yield was derived by running APSIM NG under automatic irrigation and 200 kg N ha^{-1} (no or low water and fertilizer stress). The yield gap based on crop modeling (YG-CM) was computed from the difference between simulated yield and the population mean divided by attainable yield to express the gap in percentage terms.

Random forest regression model and partial dependency plots (PDPs) (Breiman, 2001; Breiman and Cutler, 2012) were used to quantify the determinants (variable of relative importance) for yield variation in different spatial (districts) domains (Fig. 1A). PDPs were used to quantify the response between input variables and yield. In general, PDPs are equivalent to the marginal effect of individual inputs on the yield outcome.

During the analysis of four sets of on-farm experiments, through ANOVA, there was no significant effect of year and location; therefore, data were pooled for the common factors to analyze for the major factors affecting yield variation. The objective of the on-farm experiments was to identify potential entry points for closing yield gaps and to quantify the contribution of different factors on production. Thus, the on-farm experimental dataset especially comparing variety, establishment method, seeding date, N fertilizer rate, and effect of irrigation, was analysed using a meta-analysis using the R package 'meta' (Schwarzer and Schwarzer, 2012) (R Version 3.6.2) to compare (1) the variety Bijaya (treatment) vs. Gautam and Aditya (control), (2) seeding date before 30 November (treatment) vs. seeding later than 30 of November (control), (3) 100 kg ha^{-1} (treatment) vs. 60 kg N ha^{-1} (control); >100 kg N ha^{-1} (treatment) vs. 100 kg N ha^{-1} (control), (4) two irrigations (treatment) vs. one irrigation (control) (5) three irrigations (treatment) vs. two irrigations (control) (6) line seeding (treatment) vs. broadcast seeding (control). Results from simulations were analysed using descriptive statistics (mean and standard deviation), boxplots, and RMSE. Radar/spider diagrams were used to analyze the trade-offs between input use, input use efficiency, cost of production, yield and net profit among the three yield categories. For the ease of visual comparison, the values of all variables were normalized.

3. Results

3.1. Results from farm-level surveys

3.1.1. Wheat production practices and yield

The average grain yield of wheat under farmer management was 2.68 t ha^{-1} with a 28% coefficient of variance (CV) (Table 2). The average production cost was 444 USD ha^{-1} (CV of 14%), with an average net profit of 214 USD ha^{-1} (81%). The average landholding size was 0.88 ha, but with large variation (CV of 113%). The mean fertilizer application rate for nitrogen (N), phosphorus (P_2O_5) and potassium (K_2O) were 85 kg (CV of 33%), 58 kg (CV of 36%), and 0.9 (CV of 511%) kg per hectare, respectively. The average seeding rate was 159 kg seed ha^{-1} with high variation (CV of 23%). The average frequency of irrigation was 1.43, but with high variation (CV of 48%). The average rainfall during the crop growing season was 47.3 mm with large variation across districts (CV of 37%) (Table 2).

Table 2
Characterization of wheat production across the Terai districts from the household survey. Mean ± SD, and values in the brackets denote the percentage coefficient of variance (CV).

Variables	Mean (N = 1745)	Average for top 10th decile	Average for 1st-9th deciles	Average for bottom 10th decile
Grain yield (kg ha^{-1})	2677 ± 750 (28)	4081 ± 444	2693 ± 482	1595 ± 227
Net profit (USD ha^{-1})	214 ± 175 (81)	528 ± 115	215 ± 121	−18 ± 73
Production cost (USD ha^{-1})	444 ± 60 (14)	475 ± 56	446 ± 57	409 ± 60
Farm size (ha)	0.78 ± 0.88 (36)	1.13 ± 1.66	0.76 ± 0.74	0.61 ± 0.63
Seeding date	23- Nov ±7.2 (30)	20- Nov ± 4.3	22 Nov ± 5.2	24 Nov ± 3.2
Seed rate (kg ha^{-1})	160 ± 36 (24)	171 ± 37	161 ± 37	148 ± 41
Nitrogen rate (kg ha^{-1})	85 ± 28 (33)	97 ± 31	86 ± 27	71 ± 30
Phosphorus rate (kg ha^{-1})	58 ± 21 (36)	63 ± 24	59 ± 20	51 ± 22
Potassium rate (kg ha^{-1})	0.9 ± 4.6 (511)	2.5 ± 7.5	0.77 ± 4.5	0.54 ± 4.2
Number of irrigation	1.51 ± 0.6 (40)	1.84 ± 0.65	1.49 ± 0.58	1.35 ± 0.54
Seasonal rainfall (mm)	47.3 ± 17.3 (37)	–	–	–

3.1.2. Yield and profit gaps in wheat production in the western Terai region

Under farmers' management in the seven western Terai districts, the average wheat yield gap (YG-FM) was 1.60 t ha^{-1}, with yields in the individual largest plots ranging between 0.84 and 6.0 t ha^{-1}. The mean yield of the top (10th) decile was 4.1 t ha^{-1}, while the mean yield for the rest of the farmers was 2.52 t ha^{-1} suggesting a current YG-FM of 1.6 t ha^{-1} across farmer fields in the Western Terai region (Fig. 2a). These data compare with the regional simulated potential yield of 7.31 t ha^{-1}, highlighting a large potential yield gap (YG-CM) of 4.63 t ha^{-1} (i.e., 66%). Similarly, the average net profit from wheat production under farmers' management in the study region was 214 USD ha^{-1}, ranging between – 260 and + 960 USD ha^{-1} for individual plots. The mean net profit of the top (10th) decile was 527 USD ha^{-1}, suggesting a mean highest farmers' net profit gap of 348 USD ha^{-1} (Fig. 2b), with 27% of farmers having a very low net profit of <100 USD ha^{-1}.

3.1.3. Drivers of wheat grain yield

Applying Random Forest with fifteen different predictor variables derived from field surveys and secondary climatic data, the model explained 33% of yield variance (Fig. 3). N rate was the most important factor explaining yield variation, followed by the average temperature at maturity (terminal heat), the number of irrigations applied, rainfall amount, amount of seeding rate used, and the quality of seed used (i.e., whether the seed was certified or non-certified), and weed management (Fig. 3A).

To visualize interactions between the primary drivers of wheat yield, a CART tree was also constructed. Similar to the RF model, the CART showed N level as the major factor followed by water management, i.e., irrigation number and rainfall during the crop growing season and seeding rate to determine the wheat yield in the western Terai region (Fig. SI3). This analysis indicated that the N rate was the most important variable explaining wheat yield. A threshold of N rate of 64 kg ha^{-1} was determined and split into two water-related factors, i.e., rainfall amount and irrigation frequency. The lowest grain yield (2.1 t ha^{-1}) node was with N rates lower than 64 kg ha^{-1} and seasonal rainfall below 126 mm. Similarly, another node was N rates below 64 kg ha^{-1} with seasonal rainfall higher than 126 mm, where the average wheat yield was 2.56 t ha^{-1}. Also, the N rate of >64 kg ha^{-1} again split into two nodes influenced by the irrigation frequency. Farmers who had applied >64 kg N ha^{-1} with an irrigation frequency of <1.5 produced an average wheat yield of 2.7 t ha^{-1}, while farmers who applied more than one irrigation had the highest average yield (3.1 t ha^{-1}) (Fig. SI3).

3.1.4. Response of wheat grain yield to changes in individual variables

The partial dependence plot for grain yield showed that all other variables' effects remained constant at their average values; the grain yield of wheat increased by 2.86 kg ha^{-1} with each kg of N fertilizer application from 50 kg ha^{-1} up to a level of 120 kg ha^{-1}. The increment in grain yield was non-significant with increasing N fertilizer level beyond 120 kg N ha^{-1} (Fig. 3A). Regarding irrigation frequency, about 95% of the surveyed farmers applied at least one irrigation in wheat. PDP analysis suggests that additional irrigation increased grain yield by 100 kg ha^{-1} compared to farmers who have applied one irrigation (Fig. 3C). Similarly, the partial dependence plot for the seeding rate suggested that increasing the seeding rate from 100 to 150 kg ha^{-1} may be associated with a yield gain of 120 kg ha^{-1} in wheat. However, no significant yield advantage when the seeding rate increased beyond 180 kg ha^{-1} (Fig. 3D).

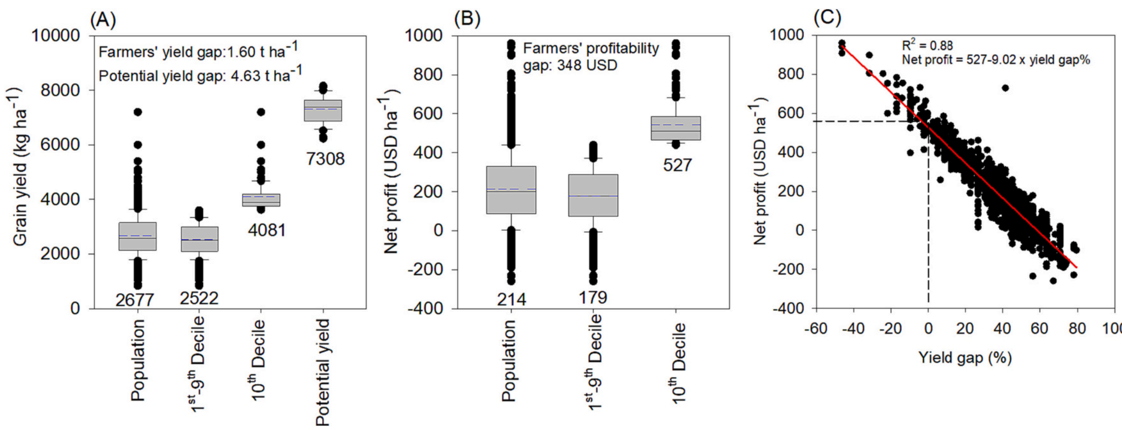

Fig. 2. Wheat grain yield (kg ha^{-1}) from the survey and crop model-based yield (A), net profit (USD ha^{-1}) from the survey (B) and the relationship between farmers' net profit gap and yield gap percentage (C). In Fig. A, farmers yield gap (YG-FM) is the difference between top 10th decile and the mean yield of all other farmers who are not in the top decile (i.e., 1st-9th deciles) and crop model based potential yield gap (YG-CM) is the difference between simulated yield and the population mean. In Fig. B, between the top (10th) decile and the rest of the farmers in the western Terai, Nepal. The dotted line indicated the mean.

3.1.5. Trade-off among input use and efficiency indicators

We examined trade-offs between production inputs and outputs and how these variables varied among different categories of farmers classified based on their yield (Fig. 4). The farmers categorized within the top (10th) decile yield had a higher net profit, had applied higher N, P, and K fertilizers rates, frequency of irrigation, seeding rates, and land-holding sizes nearly three times largest than the lowest decile, but had equivalent production cost and higher NUE and PUE than the averages for the farmers in the 2nd to 9th and the lowest performing (1st) decile (Fig. 4).

3.2. Results from on-farm experiments

3.2.1. Agronomic practices

Analysis of data from on-farm trials (3088 experimental and 1696 control treatments extracted from 102 on-farm experiments) indicated that there is considerable scope to increase wheat yield (Fig. 5). Single, non-interactive treatment results suggested that N rate had the highest impact on yield followed by irrigation management, establishment method (line seeding), and cultivation of an improved variety (Bijaya). Data also suggested that optimal N fertilizer application (100 kg N ha^{-1}) increased yield by 31%, followed by 16% by applying two irrigations, 13% by line seeding, 8% by the use of the improved variety, and by 2% with the use of optimal seeding rate (Fig. 5).

3.3. Results from simulation modeling

3.3.1. Model calibration and validation

The goodness-of-fit parameters of the APSIM model validation process showed that observed and simulated parameters matched well for yield (Fig. 6) and phenology (Table 3), indicating that the model satisfactorily simulated wheat yields in the Western Terai region of Nepal. There was close matching between simulated and measured results for days to anthesis (< 5 d), physiological maturity (< 10 d), and grain yield (< 0.7 t ha^{-1}) (Fig. 6, Table 3).

3.3.2. Long-term simulation (1984–2022)

3.3.2.1. Simulated potential wheat yield. The average simulated potential yield of wheat (averaged across eight seeding dates starting from 15 September to 01 January and nine Terai districts) was 6.84 t ha^{-1} ranging from 6.4 t ha^{-1} to 7.6 t ha^{-1} (Fig. 7A). Simulation results from 15 September to 01 January seeding dates showed potential yield varied significantly across seeding dates. Model outputs suggested that the highest yields could be obtained when wheat crop was sown on 15 November (7.4 t ha^{-1}), with yield declining by 49 kg ha^{-1} d^{-1} if seeded after 1st December (Fig. 7B). The yield obtained with 15 October seeding was not significantly different from 15 November seeding. Long-term simulations also showed a significant variation in the optimal seeding date across districts (Fig. 8). Chitwan, Kanchanpur, Kailali, Kapilbastu had the highest yield with early seeding (beginning of November), while other more southern districts had the highest wheat yield when seeding was between 1st November to 1st December (Fig. 8). The rate of yield decline after the 1st of December seeding varied across the districts, ranging from 3 to 14% (14–68 kg ha^{-1} d^{-1}) with the highest rate of decline in Kapilbastu and Bara (14%; 68 kg ha^{-1} d^{-1}) followed by a medium rate of decline (12–13%; 58–62 kg ha^{-1} d^{-1}) in Chitwan and Rupandehi and the lowest rate of decline ranging from 3 to 4%; 14–15 kg ha^{-1} d^{-1}) in Dhanusha, and Sunsari districts (Fig. 8).

3.3.2.2. Simulated wheat responses to nitrogen, irrigation, and seeding date. Under rainfed conditions, our long-term multi-location simulations suggested that wheat yield increased by 18 kg grain kg^{-1} for each kg increment in nitrogen fertilizer up to 50 kg N ha^{-1} and by 8 kg grain kg^{-1} N from 50 to 100 kg N ha^{-1} (Fig. 9A). Increased N rate beyond 100 kg ha^{-1} does not appear to be advantageous for increasing yield under rainfed conditions. With supplemental irrigation applied when soil moisture declined to 25% PAWC, yield increased by 31, 22 and 6 kg grain kg^{-1} N from 0 to 50, 50 to 100 and 100–150 kg N ha^{-1}. Simulations with supplemental irrigation applied 50% PAWC yield increased (highest) by 41, 38 and 17 kg grain kg^{-1} N from 0 to 50, 50 to 100 and 100–150 kg N ha^{-1}, respectively (Fig. 9A).

Similarly, the simulation results from fertilizer × seeding time scenarios showed that the highest N response was achieved when wheat was sown between 1st November to 1st December planted wheat, while application of >100 kg N ha^{-1} is unlikely to be beneficial for wheat planted after beginning of December (Fig. 9B). Averaged across all rates of supplementary irrigation, N application rates varied with the location where the simulated wheat yield was highest in Chitwan at <100 kg N application while the highest yield was obtained when N rate was higher than 100 kg ha^{-1} in Dhanusha (Fig. 9C). Rainfall received during the wheat growing period varies across districts, where the lowest rates are identified in Banke (100 mm) to 202 mm in Bara (Fig. 9D). As a consequence, simulated irrigation requirements varied across districts, ranging from 72 mm (Kanchanpur) to 114 mm (Kailali) under 25% PAWC and 125 mm (Kanchanpur) to 200 m (Bara) under 50% PAWC. Under 75% and 95% PAWC, irrigation requirements increased to 154–200 and 233 to 271 mm, respectively.

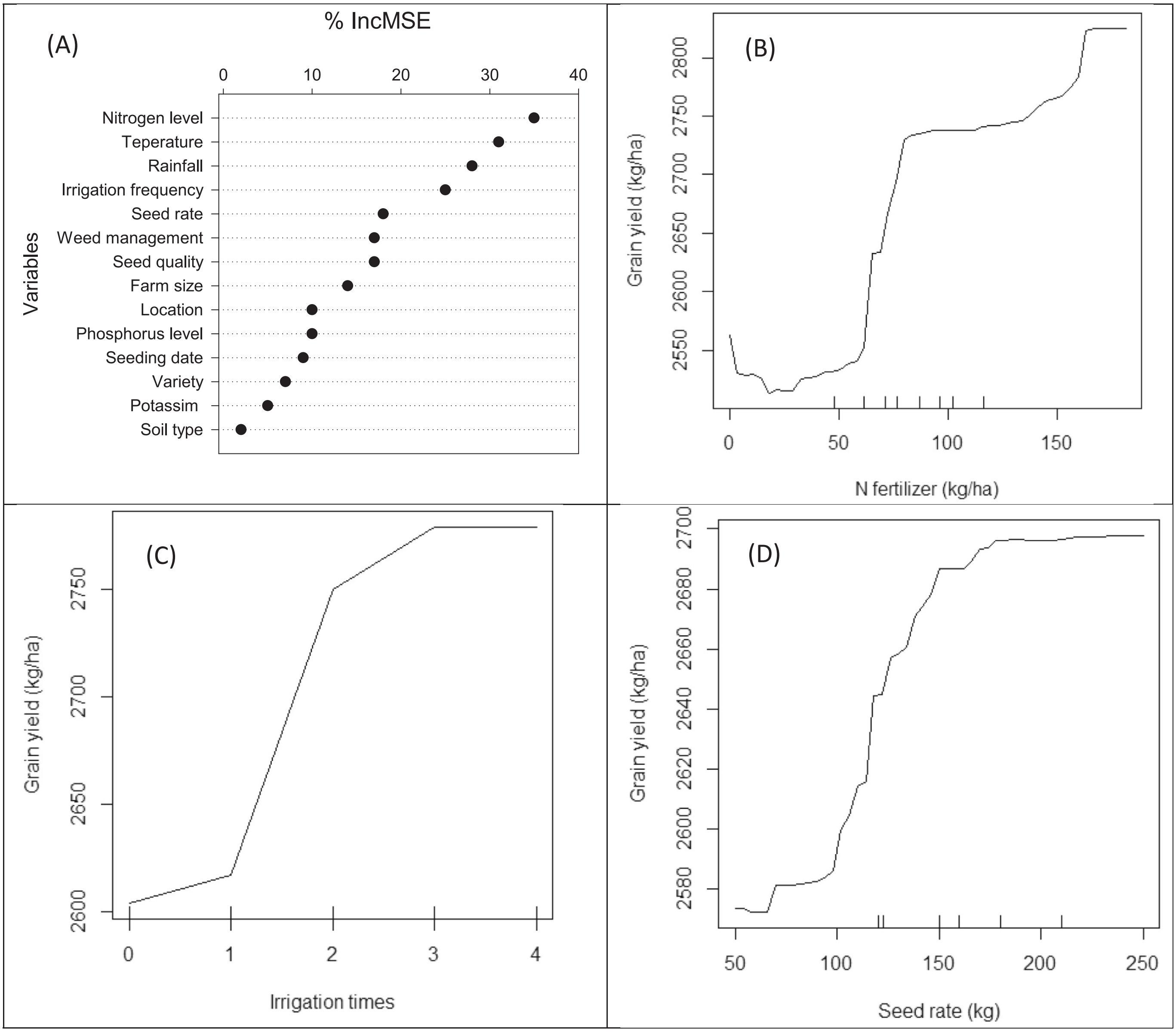

Fig. 3. Importance of different variables in explaining variation in grain yield in wheat (A), partial dependence plots of wheat for the top-ranked predictor variables, nitrogen fertilizer level (B), irrigation frequency (C), and seed rate (D) in wheat production in western Terai, Nepal. Results from the random forest (RF) models.

4. Discussion

In Nepal, wheat is a widely consumed staple food grown over 0.71 million ha (MoF, 2021). Our yield and profit gap analysis derived from surveys of 1745 farmer-managed wheat fields, results from the 3088 experimental and 1696 control treatments extracted from 102 on-farm experiments, and multi-location long-term simulations in the major wheat-growing regions of Nepal's Terai indicated that there is significant scope to improve yield and profit outcomes from wheat cultivation. Importantly, this study used a novel approach of using on-farm research generated dataset for model calibration and validation.

For high-yielding farmers, the amount of nitrogen fertilizer application followed by the average temperature at grain filling (governed by seeding time differences), number of irrigations applied, growing season rainfall, amount of seeding rate used, and the quality of seed used are primary drivers of productivity (Fig. 3). This result is supported by our long-term simulation which suggested that optimal N fertilization, timely planting, and supplementary irrigation can enhance wheat yield in the Terai (Figs. 7-9). Conversely, our survey data suggested that only 21% of farmers come close to reaching 100 kg N ha^{-1} (near the national recommendation of 120 kg N ha^{-1}) and 12% have applied no or very low N fertilizer. Both on-farm trials and long-term simulations confirmed that appropriate nitrogen fertilizer management can increase yield and farm profit (Figs. 3, 5, 9). These findings are in close agreement with Park et al. (2018), who applied a similar farm survey approach in the nearby state of Bihar, India and in some parts of the Nepal Terai, where early seeding with long maturing varieties, higher rates of N, P, and particularly K application, transitions to no-tillage for crop establishment, and encouraging more frequent irrigation were identified as major determinants for closing wheat yield gaps.

In our study, water management was identified as another important variable influencing wheat yield and farm profit (Fig. 3), where 95% of the sampled farmers applied at least one irrigation to wheat (6, 51, 38, 5, and 0% farmers applied 0, 1, 2, 3, and 4 irrigations). These results were further supported by on-farm experiments (Fig. 5), suggesting that significant yield increments could be possible through increased irrigation with the application of ~150 kg N ha^{-1}. This study used a noble approach of using on-farm participatory research generated dataset for

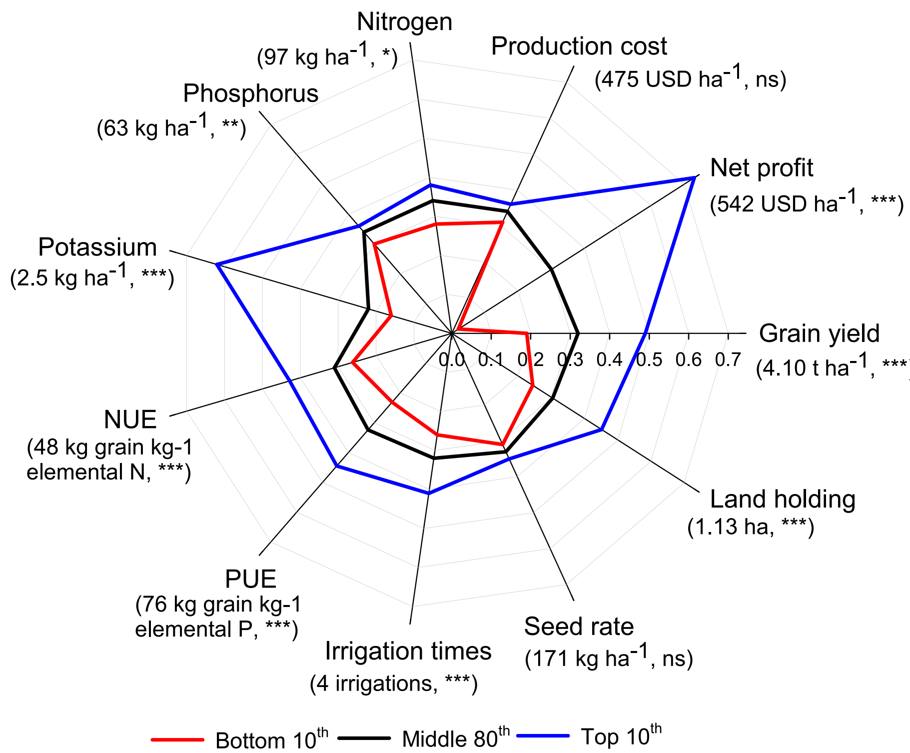

Fig. 4. Trade-offs between inputs and output performance indicators across three categories of farmers (delineated by grain yield percentile category) under farmers managed wheat production in Western Terai region of Nepal. Grain yield, net profit, NUE, PUE are output indicators, and production cost, land holding, irrigation times, N, P and K amounts are the inputs applied. All inputs and outputs values are normalized, and their values range from 0 to 1. *, **, *** and ns denote significant at $p = 0.05$, 0.01, <0.01 and non-significant, respectively analysed using ANOVA. Values in bracket are the mean of top 10th.
Note: Symbols and units for the parameter used: Grain yield = average grain yield (kg ha^{-1}); net profit = net profit (USD ha^{-1}); production cost = total production cost (USD ha^{-1}); nitrogen = nitrogen fertilizer (elemental N kg ha^{-1}); phosphorus = phosphorus fertilizer (P_2O_5, kg ha^{-1}); Potassium = potassium fertilizer (K_2O, kg ha^{-1}); NUE = nitrogen use efficiency (kg grain kg^{-1} applied N); PUE = phosphorus use efficiency (kg grain kg^{-1} elemental P); irrigation times = number of irrigation applied; seed rate = amount of seed used (kg ha^{-1}); land holding = total land holding size.

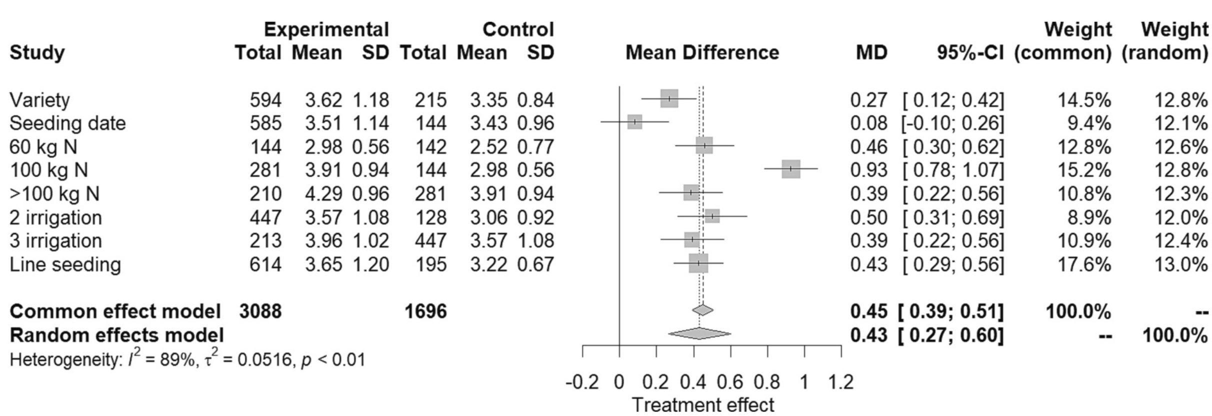

Fig. 5. The average effect of each improved practice over farmer's practice (control) on grain yield of wheat. Data were extracted from 102 on-farm experiments from 2011 to 2017 from eight districts and >30 sites (Table 1). Note: SD- Standard deviation; MD- Mean difference; CI- Confidence interval.

model calibration and validation. Our simulation study on the interaction between irrigation and N fertilizer rates showed that application of additional irrigation at 25 or 50% of PAWC can boost yield by 34% through irrigating at 25% PAWC and by 60% through irrigating at 50% PAWC (i.e., 60% closing of 66% simulated yield gap) (Fig. 9), where wheat has simulated yield of >7.31 t ha^{-1} (Fig. 2a). The national productivity of wheat is around 3.0 t ha^{-1} (FAOSTAT, 2023); our data suggest that in the Terai this can be increased significantly through supplementary irrigation at 50% PAWC combined with N fertilizer rates of 100–150 kg N ha^{-1}. Furthermore, additional irrigation at 50% of PAWC (149 ± 17 mm) can be used in locations with sufficiently readily available water supply. In contrast, in locations with less readily available water, supplementary irrigation at 25% PAWC (95 ± 13 mm) could be an appropriate benchmark for irrigation scheduling, while SI >50% PAWC may not be economical and required for the wheat crop in Terai region of Nepal. The provision of irrigation through groundwater or harvested excess water from the rainy season coupled and/or the use of surface water with efficient irrigation methods – in other words, conjunctive water management (Pandey et al., 2023) – could help to increase the availability of water to apply more than one irrigation. Conversely, despite significant public expenditure on fertilizers (Kishore et al., 2021), farmers in Nepal face a range of challenges reliably

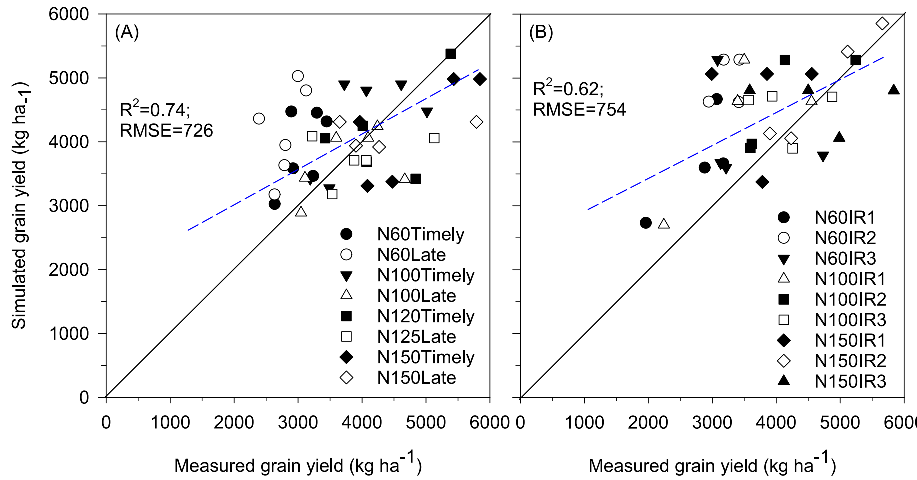

Fig. 6. Measured and simulated grain yield (kg ha^{-1}) of wheat from sowing date × N rate (on-farm experiment-I; A) and N rates × the number of irrigation (on-farm experiment-II; B). Black solid 1:1 line and blue dotted fitted regression line of observed and simulated values. IR with value in Fig. (B) is number of irrigation. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 3
Statistical analysis of model calibration and validation of different parameters of wheat.

Parameters	Mean			Standard deviation		R-square	Mean Difference	RMSEa	RMSEn	Number of observations used
	Observed	Simulated	Ratio	Observed	Simulated					
Calibration										
Anthesis (day)	105	102	0.97	5.3	2.0	0.73	−3	4	3.81	43
Maturity (day)	142	137	0.96	6.5	2.3	0.79	−5	5	3.52	43
Grain yield (kg ha^{-1})	3836	4026	1.04	880	621	0.74	190	726	18.93	43
Validation										
Anthesis (day)	101	96	0.95	5.5	4.5	0.58	−5	3	2.97	36
Maturity (day)	145	135	0.93	7.2	3.3	0.67	−10	4	2.76	36
Grain yield (kg ha^{-1})	3837	4472	1.16	899	764	0.62	635	754	19.65	36

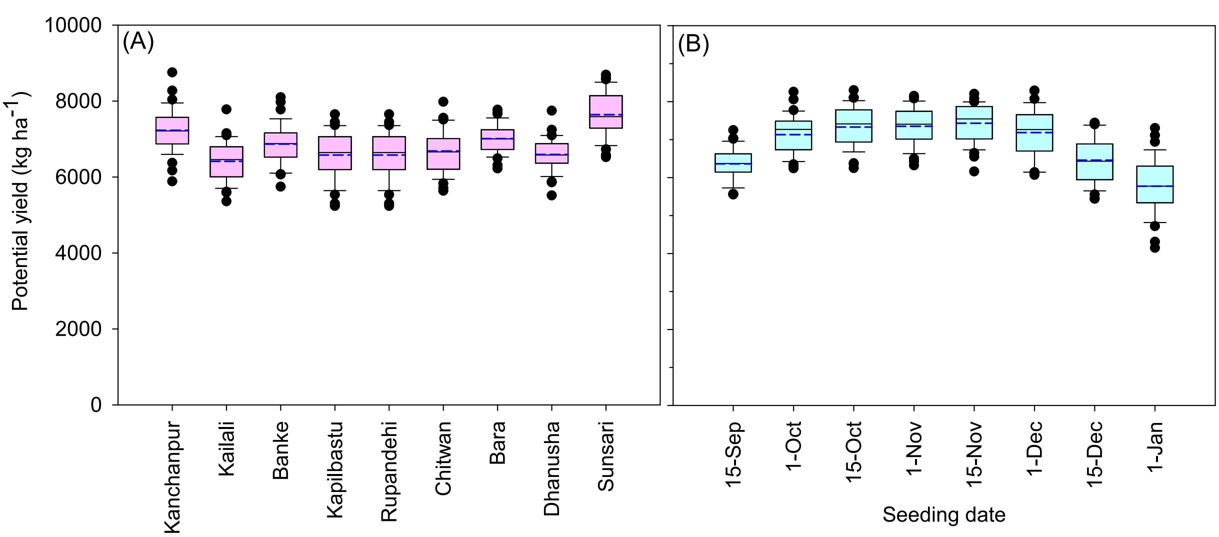

Fig. 7. Simulated yield (kg ha^{-1}) of wheat in nine different Terai districts (A) and under eight seeding dates (average of nine districts) (B). Values are with automatic irrigation (re-irrigated at 95% PAWC to reach to 100% PAWC) and 200 kg N ha^{-1} across all seeding dates from 15 September to 01 January in Fig. A and same data averaged across districts in Fig. B.

accessing fertilizers when and where they are needed (Krupnik et al., 2021). Simply recommending increased use of irrigation and fertilizers is therefore unlikely to be sufficient to stimulate change; rather, data such as those generated by this study can be used to help target district-specific refinement of fertilizer and irrigation recommendations to increase efficiency and profitability. Beyond fundamental agronomy, further efforts are needed to address regulatory obstacles, illegal trade and hoarding, and poor infrastructure that undermine effective input supply and use in Nepal (Panta, 2018; Krupnik et al., 2021).

The temperature at grain formation and filling (terminal heat stress)

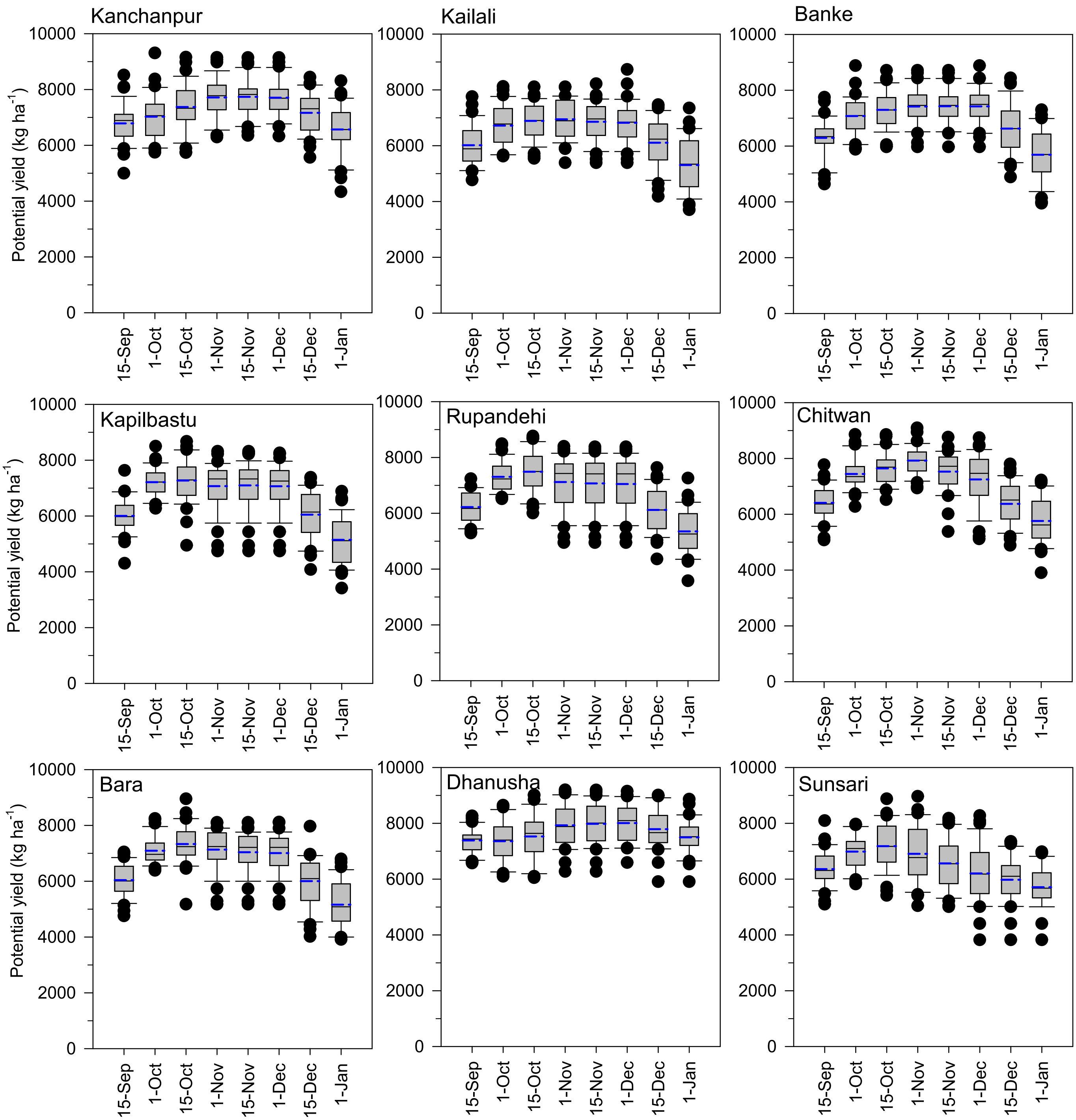

Fig. 8. Simulated yield under eight different seeding dates in nine wheat-growing Terai districts of Nepal. Values are with automatic irrigation at 95% plant available water content (PAWC) and 200 kg nitrogen ha^{-1}.

is another major factor in determining grain yield (Mondal et al., 2013). High temperatures, typically above 34 °C, affect final grain weight by reducing grain filling duration due to suppression of current photosynthesis (Al-Khatib and Paulsen, 1984), and by directly inhibiting starch biosynthesis in the endosperm (Jenner, 1994; Keeling et al., 1993). Previous research in Nepal showed that delayed seeding after November significantly reduced wheat yield, an effect mainly associated with terminal heat stress (Dubey et al., 2020; McDonald et al., 2022). Our on-farm experiments and the long-term simulation at 15-day intervals from 15 September to 01 January indicated sizeable differences in yield potential (Figs. 7, 8). The seeding date varies across locations and the late seeding after 1st week of December caused a significant yield reduction. In most districts, wheat yield starts to decline when seeding after 15 November, while the highest yield was obtained between 01 to 30 November. Similar findings were reported in other parts of the Eastern Indo-Gangetic Plain (McDonald et al., 2022) and deltaic Bangladesh (Krupnik et al., 2015). With late seeding in Nepal, hot-westerly wind, which generally starts after 15 March, can cause premature ripening and drying of wheat plants (Giri, 1998). Dubey et al. (2020) reported that advancing the seeding date in combination with the application of an additional dose of nitrogen and irrigation at the grain filling stage can reduce the effect of yield loss due to terminal heat

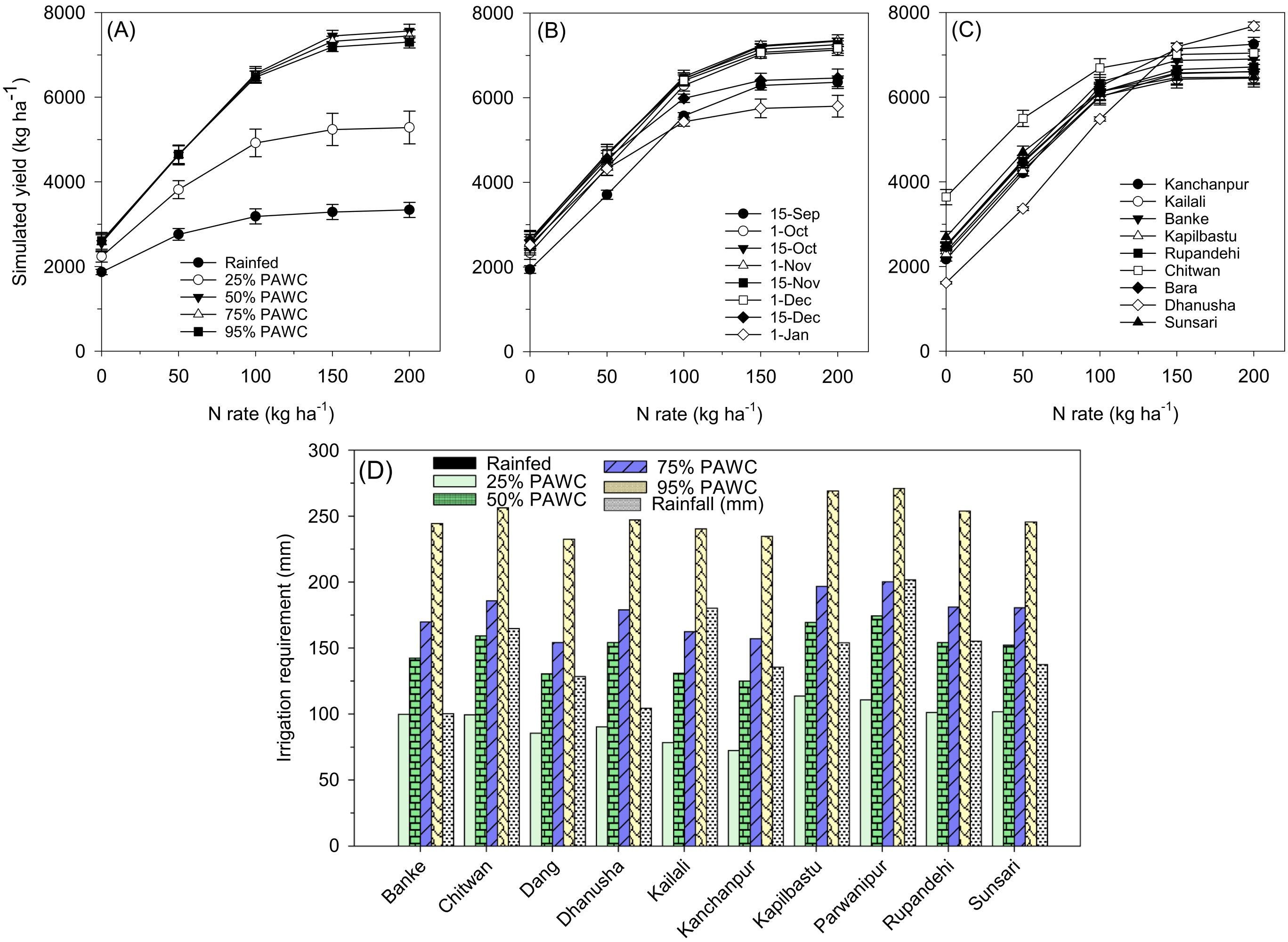

Fig. 9. Simulated wheat yield under different nitrogen application rates (N rate) and the number of irrigation (A), seeding date and N application rate (irrigation at 95% plant available water content (PAWC)) (B), N rate under two different soil types (C), and irrigation (mm) requirement in different sites (D). Long-term simulation results from nine terai districts. Fig. A values averaged across districts (9) and seeding dates (8); Figs. B and C values with automatic irrigation at 95% PAWC.

stress in India.

Our survey data suggested that the top decile farmers, based on yield performance, are more efficient, applied more fertilizer input and irrigation, and obtained higher profit than other farmers (Fig. 6). This suggests that there is a possibility of enhancing grain yield and profit while improving efficiency for nutrient and water use. For benchmarking, previous research has used input use and efficiency indicators among the top 10th decile farmers in surveys to set aspirational targets for improved production (Devkota et al., 2021; Devkota et al., 2019a, 2019b; Devkota and Yigezu, 2020; Stuart et al., 2016), although not all farmers are likely to have easy and reliable access to fertilizers or irrigation in Nepal (Krupnik et al., 2021).

This study identified low-cost technologies, including appropriate varieties and optimal seeding rates as important factors for increasing wheat yield and farm profit. On average, farmers who used certified seed also produced 9% more yield than those who did not; however, only 50% of farmers in our survey used certified seed. This suggests that governmental programs and the private sector need to consider mechanisms to increase the availability of quality seed and suitable varieties as components of low-cost, more easily accessible practices needed to close the yield gaps (Krupnik et al., 2021). Similarly, following seed, better weed management was also identified by Random Forest analysis as an important causal factor in determining wheat yield. Previous research in Nepal has shown that farmers with better crop establishment and who used herbicide in their wheat fields had a 19% higher yield than those who did not apply herbicide for weed management (Devkota et al., 2019a, 2019b). If weeds are not well managed, losses of up to 5–70% are possible (Devkota et al., 2019a, 2019b; Ranjit et al., 2006). In this study, 6.8% of farmers applied herbicide for weed management; these farmers also tended to have higher yields, indicating the potential for careful and appropriate herbicide use (Chauhan et al., 2012; Rao et al., 2020), though reliance on herbicide alone is unlikely to be appropriate. Rather, herbicide use must be a component of integrated weed management approaches in Nepal (Krupnik et al., 2021), with caution applied to ensure the rotation of appropriate active ingredients and integration of integrated weed control options.

As our survey data was collected during the 2016/17 growing season, subsequent global challenges, including COVID-19 and its impact on agricultural systems in Nepal (Dixon et al., 2021) and the Russia-Ukraine conflict, may slightly affect our profitability assessment. However, the fertilizer supply in Nepal has long been challenging (Kishore et al., 2021; Krupnik et al., 2021) – even before COVID-19 and the Russia-Ukraine conflict. However, as a standard methodology survey for selecting sites and samples, and in combination with simulations of yield variability across years that showed relatively consistent results in our study (Fig. 8), we suggest that our data is sufficiently representative of general conditions in Nepal to draw appropriate conclusions. Despite the overall good agreement between farmers' reported yield and crop-cut yield, there are few fields in which there is a large disagreement (42% of the total) where farmer-reported yields were larger than those from crop cuts' (Fig. SI1), hence it also needs to be well considered for such a study. Paliwal and Jain (2020) reported that although self-reported yield estimates are faster and lower cost, they likely are not adequate data sources to train yield prediction models and should be used with caution. The long-term simulation used NASA Power weather data adjusted with the measured data from one location (Banke district) (Fig. SI2). NASA Power data may contain uncertainties, particularly in regions with limited validation with ground-based observations. However, as the simulation was carried out for the similar geographic condition "Terai region' (Fig. 1), climate data did not influence the results.

The higher yields with no or a minimum number of tillage events indicated that there may be the opportunity to reduce the yield gaps in yield and net profit through the adoption of conservation tillage practices in the rainfed systems of Nepal, where intensive tillage and cereal mono-cropping are predominantly practiced (Krupnik et al., 2021). Previous on-station research documented that no-tillage can help to enhance grain yield while contributing to improved soil quality and water use efficiency while also reducing the production cost in Eastern Gangetic Plane (Choudhary et al., 2018b; Choudhary et al., 2018a; Gathala et al., 2014; Singh et al., 2016). Integrated agronomic practices (Devkota et al., 2021) and improved fertilizer management practices (Devkota et al., 2018) are important to close the yield and profit gaps in Nepal.

5. Conclusions

This study demonstrated how a mixed-methods approach that combines household surveys, on-farm experiments, and long-term crop simulation can identify actionable ways to increase wheat yield and profitability in the Terai of Nepal. Machine learning analytics suggest that on-farm differences in nitrogen management followed by temperature stress during grain filling (terminal heat stress) and the number of irrigations were the principal drivers of variation in wheat yield and profitability. Among the various combinations of agronomic options, advancing seeding by 7–10 days (from the average farmers' seeding date), with line seeding, a slight increase of approximately 20 kg ha^{-1} of nitrogen fertilizer, and two additional irrigations were found to be beneficial compared to prevailing farmers' practices. These bundled agronomic solutions are likely to help sustainably reduce the existing 63% productivity gap between the highest yielding and average field in the region. Integrating good agronomic practices is most promising to close yield and profit gaps fully, although small changes to single management factors can also pay dividends. By uncovering drivers of yield gaps and placing additional research emphasis on how different intensification options link to economic and environmental management goals, wheat farmers in Nepal can be better placed to match improved yield with profitability.

Declaration of Competing Interest

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

Data availability

Data will be made available on request.

Acknowledgments

This work was supported by the Cereal Systems Initiative for South Asia (CSISA), funded by the U.S. Agency for International Development (USAID) (Grant no. BFS-G-11-00002). We also acknowledge the CSISA Nepal team and collaborating farmers involved in this study. We acknowledge the One CGIAR Initiatives- EiA and CGIAR Regional Initiative F2R-CWANA for the support to develop this manuscript. The contents of this paper do not necessarily reflect the views of USAID or CGIAR.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.agsy.2023.103804.

References

Al-Khatib, K., Paulsen, G.M., 1984. Mode of high temperature injury to wheat during grain development. Physiol. Plant. 61, 363–368.

Balwinder-Singh, Humphreys, E., Gaydon, D.S., Eberbach, P.L., 2016. Evaluation of the effects of mulch on optimum sowing date and irrigation management of zero till wheat in Central Punjab, India using APSIM. F. Crop. Res. 197, 83–96. https://doi.org/10.1016/j.fcr.2016.08.016.

Batjes, N.H., 2012. ISRIC-WISE derived soil properties on a 5 by 5 arc-minutes global grid (ver. 1.2). In: ISRIC-World Soil Information. https://library.wur.nl/WebQuery/wurpubs/fulltext/206736.

Breiman, L., 2001. Random forests. Mach. Learn. 45, 5–32.

Breiman, L., 2017. Classification and Regression Trees. Routledge.

Breiman, L., Cutler, A., 2012. Breiman and Cutler's random forests for classification and regression. In: Packag. "randomForest" 29. https://doi.org/10.5244/C.22.54.

Chaki, A.K., Gaydon, D.S., Dalal, R.C., Bellotti, W.D., Gathala, M.K., Hossain, A., Menzies, N.W., 2022. How we used APSIM to simulate conservation agriculture practices in the rice-wheat system of the eastern Gangetic Plains. F. Crop. Res. 275, 108344 https://doi.org/10.1016/j.fcr.2021.108344.

Chauhan, B.S., Mahajan, G., Sardana, V., Timsina, J., Jat, M.L., 2012. Productivity and sustainability of the rice–wheat cropping system in the indo-gangetic plains of the indian subcontinent: problems, opportunities, and strategies. In: Donald, L.S. (Ed.), Advances in Agronomy. Academic Press, pp. 315–369. https://doi.org/10.1016/B978-0-12-394278-4.00006-4.

Choudhary, M., Datta, A., Jat, H.S., Yadav, A.K., Gathala, M.K., Sapkota, T.B., Das, A.K., Sharma, P.C., Jat, M.L., Singh, R., Ladha, J.K., 2018a. Changes in soil biology under conservation agriculture based sustainable intensification of cereal systems in Indo-Gangetic Plains. Geoderma 313, 193–204. https://doi.org/10.1016/j.geoderma.2017.10.041.

Choudhary, M., Jat, H.S., Datta, A., Yadav, A.K., Sapkota, T.B., Mondal, S., Meena, R.P., Sharma, P.C., Jat, M.L., 2018b. Sustainable intensification influences soil quality, biota, and productivity in cereal-based agroecosystems. Appl. Soil Ecol. 126, 189–198. https://doi.org/10.1016/j.apsoil.2018.02.027.

Devkota, M., Yigezu, Y.A., 2020. Explaining yield and gross margin gaps for sustainable intensification of the wheat-based systems in a Mediterranean climate. Agric. Syst. 185, 102946.

Devkota, K.P., Devkota, M., Khadka, L., Khadka, A., Paudel, G., Acharya, S., McDonald, A.J., 2018. Nutrient responses of wheat and rapeseed under different crop establishment and fertilization methods in contrasting agro-ecological conditions in Nepal. Soil Tillage Res. 181, 46–62. https://doi.org/10.1016/j.still.2018.04.001.

Devkota, M., Devkota, K.P., Acharya, S., McDonald, A.J., 2019a. Increasing profitability, yields and yield stability through sustainable crop establishment practices in the rice-wheat systems of Nepal. Agric. Syst. 173 https://doi.org/10.1016/j.agsy.2019.03.022.

Devkota, K.P., Pasuquin, E., Elmido-Mabilangan, A., Dikitanan, R., Singleton, G.R., Stuart, A.M., Vithoonjit, D., Vidiyangkura, L., Pustika, A.B., Afriani, R., Listyowati, C.L., Keerthisena, R.S.K., Kieu, N.T., Malabayabas, A.J., Hu, R., Pan, J., Beebout, S.E.J., 2019b. Economic and environmental indicators of sustainable rice cultivation: a comparison across intensive irrigated rice cropping systems in six Asian countries. Ecol. Indic. 105, 199–214. https://doi.org/10.1016/j.ecolind.2019.05.029.

Devkota, K.P., Devkota, M., Moussadek, R., Nangia, V., 2023. Genotype × environment × agronomic management interaction to enhance wheat yield in the Mediterranean rainfed environments of Morocco: II. Process based modeling. European Journal of Agronomy 151, 126973. https://doi.org/10.1016/j.eja.2023.126973.

Devkota, K.P., Devkota, M., Paudel, G.P., McDonald, A.J., 2021. Coupling landscape-scale diagnostics surveys, on-farm experiments, and simulation to identify entry points for sustainably closing rice yield gaps in Nepal. Agric. Syst. 192, 103182.

Devkota, K.P., Timsina, J., Amgain, L.P., Devkota, M., 2022. Potential of crop simulation models to increase food and nutrition security under a changing climate in Nepal. In: Achieving Food, Nutrition, and Livelihood Security: Principles and Practices for Sustainable Farming Systems in Nepal (Accepted), p. 16.

Dixon, J.M., Weerahewa, J., Hellin, J., Rola-Rubzen, M.F., Huang, J., Kumar, S., Das, A., Qureshi, M.E., Krupnik, T.J., Shideed, K., Jat, M.L., Prasad, P.V.V., Yadav, S., Irshad, A., Asanaliev, A., Abugalieva, A., Karimov, A., Bhattarai, B., Balgos, C.Q., Benu, F., Ehara, H., Pant, J., Sarmiento, J.M.P., Newby, J.C., Pretty, J., Tokuda, H., Weyerhaeuser, H., Digal, L.N., Li, L., Sarkar, M.A.R., Abedin, M.Z., Schreinemachers, P., Grafton, Q., Sharma, R.C., Saidzoda, S., Lopez-Ridaura, S., Coffey, S., Kam, S.P., Win, S.S., Praneetvatakul, S., Maraseni, T., Touch, V., Liang, W.-L., Saharawat, Y.S., Timsina, J., 2021. Response and resilience of Asian

agrifood systems to COVID-19: an assessment across twenty-five countries and four regional farming and food systems. Agric. Syst. 193, 103168.
Dubey, R., Pathak, H., Chakrabarti, B., Singh, S., Gupta, D.K., Harit, R.C., 2020. Impact of terminal heat stress on wheat yield in India and options for adaptation. Agric. Syst. 181, 102826.
FAOSTAT, 2023. United Nations Food and Agricultural Organisation [WWW Document].
Gathala, M.K., Kumar, V., Sharma, P.C., Saharawat, Y.S., Jat, H.S., Singh, M., Kumar, A., Jat, M.L., Humphreys, E., Sharma, D.K., Sharma, S., Ladha, J.K., 2014. Reprint of "optimizing intensive cereal-based cropping systems addressing current and future drivers of agricultural change in the Northwestern Indo-Gangetic Plains of India.". Agric. Ecosyst. Environ. 177, 33–46. https://doi.org/10.1016/j.agee.2013.06.002.
Gaydon, D.S., Balwinder-Singh, Wang, E., Poulton, P.L., Ahmad, B., Ahmed, F., Akhter, S., Ali, I., Amarasingha, R., Chaki, A.K., Chen, C., Choudhury, B.U., Darai, R., Das, A., Hochman, Z., Horan, H., Hosang, E.Y., Kumar, P.V., Khan, A.S.M.M.R., Laing, A.M., Liu, L., Malaviachichi, M.A.P.W.K., Mohapatra, K.P., Muttaleb, M.A., Power, B., Radanielson, A.M., Rai, G.S., Rashid, M.H., Rathanayake, W.M.U.K., Sarker, M.M.R., Sena, D.R., Shamim, M., Subash, N., Suriadi, A., Suriyagoda, L.D.B., Wang, G., Wang, J., Yadav, R.K., Roth, C.H., 2017. Evaluation of the APSIM model in cropping systems of Asia. F. Crop. Res. 204, 52–75. https://doi.org/10.1016/j.fcr.2016.12.015.
Giri, G.S., 1998. Surface/relay planting: an option for planting wheat on time in the lower wetlands of the Tarai, Nepal. In: Rice–Wheat Research End-of-Project Workshop, p. 57.
Holzworth, D.P., Huth, N.I., deVoil, P.G., Zurcher, E.J., Herrmann, N.I., McLean, G., Chenu, K., van Oosterom, E.J., Snow, V., Murphy, C., Moore, A.D., Brown, H., Whish, J.P.M., Verrall, S., Fainges, J., Bell, L.W., Peake, A.S., Poulton, P.L., Hochman, Z., Thorburn, P.J., Gaydon, D.S., Dalgliesh, N.P., Rodriguez, D., Cox, H., Chapman, S., Doherty, A., Teixeira, E., Sharp, J., Cichota, R., Vogeler, I., Li, F.Y., Wang, E., Hammer, G.L., Robertson, M.J., Dimes, J.P., Whitbread, A.M., Hunt, J., van Rees, H., McClelland, T., Carberry, P.S., Hargreaves, J.N.G., MacLeod, N., McDonald, C., Harsdorf, J., Wedgwood, S., Keating, B.A., 2014. APSIM - evolution towards a new generation of agricultural systems simulation. Environ. Model Softw. 62, 327–350. https://doi.org/10.1016/j.envsoft.2014.07.009.
Hothorn, T., Hornik, K., Strobl, C., Zeileis, A., Hothorn, M.T., 2015. Package 'party.' *Package Reference Manual for Party*, p. 37, Version 0.9-998, 16.
Jenner, C.F., 1994. Starch synthesis in the kernel of wheat under high temperature conditions. Funct. Plant Biol. 21, 791–806.
Joshi, K.D., Devkota, K.P., Harris, D., Khanal, N.P., Paudyal, B., Sapkota, A., Witcombe, J.R., 2012. Participatory research approaches rapidly improve household food security in Nepal and identify policy changes required for institutionalisation. Field Crop Res. 131, 40–48. https://doi.org/10.1016/j.fcr.2012.03.001.
Keating, B.A., Carberry, P.S., Hammer, G.L., Probert, M.E., Robertson, M.J., Holzworth, D., Huth, N.I., Hargreaves, J.N.G., Meinke, H., Hochman, Z., McLean, G., Verburg, K., Snow, V., Dimes, J.P., Silburn, M., Wang, E., Brown, S., Bristow, K.L., Asseng, S., Chapman, S., McCown, R.L., Freebairn, D.M., Smith, C.J., 2003. An overview of APSIM, a model designed for farming systems simulation. Eur. J. Agron. 18, 267–288. https://doi.org/10.1016/S1161-0301(02)00108-9.
Keeling, P.L., Bacon, P.J., Holt, D.C., 1993. Elevated temperature reduces starch deposition in wheat endosperm by reducing the activity of soluble starch synthase. Planta 191, 342–348.
Kishore, A., Alvi, M., Krupnik, T.J., 2021. Development of balanced nutrient management innovations in South Asia: lessons from Bangladesh, India, Nepal, and Sri Lanka. Glob. Food Sec. 28, 100464.
Krupnik, T.J., Ahmed, Z.U., Timsina, J., Yasmin, S., Hossain, F., Mamun, A., McDonald, A.J., 2015. Untangling crop management and environmental influences on wheat yield variability in Bangladesh: an application non-parametric approaches. Agric. Syst. 139, 166–179.
Krupnik, T.J., Timsina, J., Devkota, K.P., Tripathi, B.P., Karki, T.B., Urfels, A., Gaihre, Y. K., Choudhary, Dyutiman Beshir, Pandey, A.R., Vishnu Prasad Brown, B., Gartaula, H., Shahrina, Sumona Ghimire, 2021. Agronomic, socio-economic, and environmental challenges and opportunities in Nepal ' s cereal-based farming systems. In: Advances in Agronomy, 1st ed. Elsevier Inc. https://doi.org/10.1016/bs.agron.2021.06.004.
Ladha, J.K., Himanshu, P., Krupnik, T.J., Six, J., van Kessel, C., 2005. Efficiency of fertilizer nitrogen in cereal production: retrospects and prospects. Adv. Agron. 87, 85–156.
Liaw, A., Wiener, M., 2002. Classification and Regression by randomForest, 2. R News, pp. 18–22.
Lobell, D.B., Cassman, K.G., Field, C.B., 2009. Crop yield gaps: their importance, magnitudes, and causes. Annu. Rev. Environ. Resour. 34, 179–204.
McDonald, A.J., Keil, A., Srivastava, A., Craufurd, P., Kishore, A., Kumar, V., Paudel, G., Singh, S., Singh, A.K., Sohane, R.K., 2022. Time management governs climate resilience and productivity in the coupled rice–wheat cropping systems of eastern India. Nat. Food 3, 542–551.
MoF, 2021. Economic Survey 2020/21. Government of Nepal, Ministry of Finance, Singh Durbar, Kathmandu, Nepal.
Mondal, S., Singh, R.P., Crossa, J., Huerta-Espino, J., Sharma, I., Chatrath, R., Singh, G. P., Sohu, V.S., Mavi, G.S., Sukaru, V.S.P., Kalappanavarg, I.K., Mishra, V.K., Hussain, M., Gautam, N.R., Uddin, J., Barma, N.C.D., Hakim, A., Joshi, A.K., 2013. Earliness in wheat: a key to adaptation under terminal and continual high temperature stress in South Asia. Field Crop Res. 151, 19–26.
NARC, 2014. Released and Registered Crop Varieties in Nepal (1960-2013). National Agriculture Research Council (NARC). Publication No. 0040-2013/14.
NASA POWER, 2023. Prediction of Worldwide Energy Resource [WWW Document]. URL. https://power.larc.nasa.gov/common/php/POWER_ParametersAgro.php (accessed 2.05.23).
Paliwal, A., Jain, M., 2020. The accuracy of self-reported crop yield estimates and their ability to train remote sensing algorithms. Front. Sustain. Food Syst. 4, 25.
Pandey, V.P., Shrestha, N., Urfels, A., Ray, A., Khadka, M., Pavelic, P., McDonald, A.J., Krupnik, T.J., 2023. Implementing conjunctive management of water resources for irrigation development: a framework applied to the southern plain of Western Nepal. Agric. Water Manag. 283, 108287.
Panta, H.K., 2018. Supply chain of subsidized chemical fertilizers in Nepal. J. Inst. Agric. Anim. Sci. 35, 9–20. https://doi.org/10.3126/jiaas.v35i1.22509.
Park, A.G., Davis, A.S., McDonald, A.J., 2018. Priorities for wheat intensification in the eastern indo-Gangetic Plains. Glob. Food Sec. 17, 1–8.
Paudel, G., McDonald, A.J., 2021. Data on Identifying Sustainable Wheat Productivity Drivers in Nepal's Terai doi: hdl:11529/10548615.
Paudel, G., Maharjan, S., Guerena, D., Rai, A., McDonald, A.J., 2017. Nepal Rice Crop Cut and Survey Data 2016.
Ranjit, J.D., Bellinder, R.R., Hobbs, P., Rajbhandari, N.K., Kataki, P., 2006. Mapping Phalaris minor under the rice-wheat cropping system in different agro-ecological regions of Nepal. Nepal Agric. Res. J. 7, 54–63.
Rao, A.N., Singh, R.G., Mahajan, G., Wani, S.P., 2020. Weed research issues, challenges, and opportunities in India. Crop Prot. 134, 104451.
Schwarzer, G., Schwarzer, M.G., 2012. Package 'meta, 9. The R Foundation for Statistical Computing, p. 27.
Singh, V.K., Yadvinder-Singh, Dwivedi, Singh, S.K., Majumdar, K., Jat, M.L., Mishra, R. P., Rani, M., 2016. Soil physical properties, yield trends and economics after five years of conservation agriculture based rice-maize system in north-western India. Soil Tillage Res. 155, 133–148. https://doi.org/10.1016/j.still.2015.08.001.
Stuart, A.M., Pame, A.R.P., Silva, J.V., Dikitanan, R.C., Rutsaert, P., Malabayabas, A.J.B., Lampayan, R.M., Radanielson, A.M., Singleton, G.R., 2016. Yield gaps in rice-based farming systems: insights from local studies and prospects for future analysis. F. Crop. Res. 194, 43–56.
Timsina, J., Humphreys, E., 2006. Performance of CERES-Rice and CERES-wheat models in rice–wheat systems: a review. Agric. Syst. 90, 5–31.
Timsina, J., Dutta, S., Devkota, K.P., Chakraborty, S., Neupane, R.K., Bista, S., Amgain, L. P., Majumdar, K., 2022. Assessment of nutrient management in major cereals : yield prediction energy-use efficiency and greenhouse gas emission. Curr. Res. Environ. Sustain. 4, 100147 https://doi.org/10.1016/j.crsust.2022.100147.
Van Ittersum, M.K., Cassman, K.G., Grassini, P., Wolf, J., Tittonell, P., Hochman, Z., 2013. Yield gap analysis with local to global relevance—a review. F. Crop. Res. 143, 4–17.
Yang, J.M., Yang, J.-Y., Liu, S., Hoogenboom, G., 2014. An evaluation of the statistical methods for testing the performance of crop models with observed data. Agric. Syst. 127, 81–89.
Zhao, G., Bryan, B.A., Song, X., 2014. Sensitivity and uncertainty analysis of the APSIM-wheat model: interactions between cultivar, environmental, and management parameters. Ecol. Model. 279, 1–11. https://doi.org/10.1016/j.ecolmodel.2014.02.003.