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Improved nutrient management in cereals using Nutrient Expert and machine learning tools: Productivity, profitability and nutrient use efficiency

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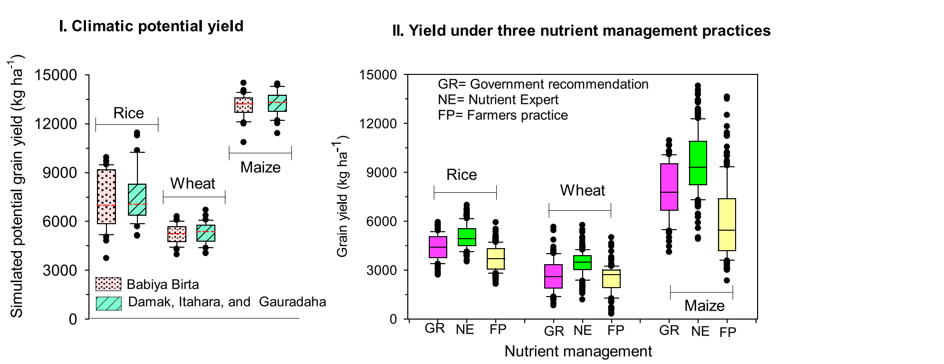
HIGHLIGHTS

- Factors influencing the low and variable grain yields of rice, wheat, and maize in the eastern Gangetic Plains are not fully understood
- Study assessed nutrient management options, estimation of yield potential and yield gaps, and causes of yield variability in 600 on-farm trials
- APSIM Model estimated potential yield and yield gaps and identified optimum planting dates.
- Random Forest identified nutrient uptake as important variable explaining yield variability.
- Nutrient Expert® recommendation can increase yield, gross returns and nutrient use efficiency over farmers' practice and government recommendation.

GRAPHICAL ABSTRACT



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ABSTRACT

CONTEXT: Smallholder farmers of the Eastern Indo-Gangetic Plains (EIGP) of South Asia rely mainly on cereal-based cropping systems to meet the food and nutritional demand and support their livelihood. Yet the

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productivity of the major cereals - rice, wheat, and maize - in the region are far lower than their potential. Nutrient management plays a crucial role in improving cereal yields and economic return, and continued improvement in nutrient management practices and their on-farm implementation is required to develop locally relevant solutions that are site-specific, easy-to-develop and geared towards system resilience.

OBJECTIVES: The objective of the study was to conduct the comparative assessment of three nutrient management strategies for the three major cereals considering productivity, profitability and nutrient use efficiencies (NUE); estimate their potential yields and yield gaps; and explain the causes of yield variability across farmer-participatory on-farm trials in the EIGP of Nepal.

METHODS: We compared three nutrient management strategies (farmer's fertilizer practice- FP, government recommendation -GR, and Nutrient Expert®- NE-based recommendation), in 600 on-farm trials. We used the NE DSS tool, APSIM – a cropping system simulation model, and machine learning (ML) approaches (Linear Mixed Effect model -LME; and Random Forest model - RF) for the three cereals using data from those trials. The NE and APSIM were chosen due to simplicity in use and their wider evaluation and application in fertilizer recommendation yield prediction; RF was chosen due to its robustness in predictive ability and identifying and ranking factors determining yield or other variables of interest.

RESULTS: The NE-based fertilizer recommendations for maize, wheat and rice increased yield by about 3.5, 1.4, and 1.3 t ha^{-1} respectively, increased profits, and improved NUE over FP or GR. The risk analysis showed that at a given probability level, NE always resulted in higher yields of all cereals than GR or FP. APSIM identified 25th June as optimum transplanting date for rice and 10th December as optimum sowing date for maize and wheat and simulated long-term average potential yield of 7–7.5, 5–5.5 and 13–13.3 t ha^{-1} respectively for rice, wheat and maize. There were larger yield gaps between PY and FP (2.6–8.5 t ha^{-1}) than PY and NE (2.0–3.7 t ha^{-1}) across crops and villages. The LME model showed highly significant treatment and location effects for grain yield of all cereals. The point estimate of the difference for grain yield as estimated by Tukey's HSD test was highest for NE-FP and lowest for GR-FP for all crops. The RF model identified grain N uptake for rice and grain P and K uptakes for wheat and maize as most influential factors contributing to their grain yield under each nutrient management strategy.

CONCLUSIONS: The NE-based nutrient management had significant effects over FP and GR leading to positive changes on yield and economic performance under varied growing environments.

SIGNIFICANCE: These findings based on novel tools and approaches have important policy implications for increasing food security and profits from the major cereals by refining or improving the GR or FP and increasing their NUE in Nepal. Studies with larger sample size across varied agro-climatic zones in the EIGP and much of South Asia would help policy makers consider DSS tools and ML approaches suitable for upscaling and large-scale adoption by smallholder farmers.

1. Introduction

Food and nutritional insecurities are major global concerns, especially for underdeveloped and developing countries, affecting more than 3 billion people every day (FAO et al., 2018; WFP, 2019). Achieving the three Sustainable Development Goals (SDGs) of the United Nations — eradicating poverty (Goal 1); ending hunger, achieving food security, and improving nutrition (Goal 2); and achieving good health and well-being (Goal 3) – by 2030 would require a 60–110% increase in global agricultural production (FAO et al., 2018). This would largely be possible by increasing the current yields at farmers' fields and closing the gaps between potential and farmer's yields, especially for major staple cereals - rice, wheat and maize (Lobell et al., 2009; van Ittersum et al., 2013; Pradhan et al., 2015).

Nutrient management plays a significant role in the improvement of cereal production, with potential to double the farm yields, especially in smallholder farming systems (Timsina and Connor, 2001; Devkota et al., 2016; Majumdar et al., 2016; Dutta et al., 2020; Amgain et al., 2021). Farmers' management practices in South Asia vary widely due to large variations in soil, weather, cropping systems, and farmers' socio-economic conditions creating large differences in indigenous nutrient supply (INS) among farmers' fields, and even between parcels within a field (Dobermann et al., 2002; Dobermann, 2007). However, the conventional fertilizer recommendations do not capture such variations adequately. In most cases, fertilizer rates determined by the national- or district-level government organizations are blanket recommendations for a region or district, without factoring the site-specific soil and weather conditions, crop management practices, crop varieties, etc. Such recommendations often lead to low nutrient-use efficiency (NUE) and reduced profitability, and may increase environmental risks associated with loss of unutilized nutrients through emissions or leaching (Dobermann, 2007; Timsina et al., 2010; Xu et al., 2016; Rurinda et al., 2020).

The 4R Nutrient Stewardship concept of applying the right rate of fertilizers at the right time through a right source and by the right method aids in application of site-specific nutrient management (SSNM) principles. Nutrient Expert® (NE) decision support tool for cereals was developed based on the 4R stewardship concept as a recommendation approach with a backbone of SSNM (Dobermann et al., 2002; Roberts, 2007; Pampolino et al., 2012a; Ray et al., 2017). On-farm use of the NE tool-based fertilizer recommendation significantly improved yield (Pampolino et al., 2012a; Xu et al., 2014; Majumdar et al., 2016; Mandal et al., 2016; Xu et al., 2016; Dutta et al., 2020; Rurinda et al., 2020; Amgain et al., 2021), NUE (Pampolino et al., 2012a; Xu et al., 2016; Zhang et al., 2017; Rurinda et al., 2020; Amgain et al., 2021), energy-use efficiency (Zhang et al., 2017; Sapkota et al., 2021), farm profitability and soil health (Mandal et al., 2016; Amgain et al., 2021), while reducing environmental footprint of fertilizer use (Zhang et al., 2017; Sapkota et al., 2021) in South and SE Asia, China and Sub-Saharan Africa. The NE tool has also been used for precision nutrient management for optimal fertilization that integrates the use of mineral fertilizers and organic amendments for long-term sustainability of the crops and cropping systems (Sapkota et al., 2014).

An important factor for variation in crop yields in farmers' fields is climate, and such variability could result in low yields and food insecurity (Wang et al., 2018). Nutrient management and climate factors act together to sustain crop production; therefore, it is necessary to understand the interaction between these two drivers of crop production. Process-based crop growth simulation models are used to estimate potential yield for any location or regions within a country (Bouman et al., 2001; Jones et al., 2003; Holzworth et al., 2014). Likewise, for investigating multiple interactions among the outcomes, the explanatory variables often demand adaptive and non-parametric multivariate analyses, due to their ability to negotiate non-linear relationships, thus overcoming the limitations of Euclidian distance based general linear models (Krupnik et al., 2015b; Dutta et al., 2020). Various studies have shown that the applications of machine learning (ML) techniques, such as linear mixed effects (LME) models, classification and regression trees, and Random Forest (RF) can be useful in determining and ranking the relative importance of factors contributing to cereal yields and yield gaps in the Eastern Indo-Gangetic Plain (EIGP) of South Asia (Banerjee et al., 2014; Krupnik et al., 2015b; Dutta et al., 2020) and globally (Jeong et al., 2016; Paudel et al., 2021).

Rice, wheat, and maize are the main three staple cereal crops in Nepal in terms of area, production, and calorie and protein supply to the Nepalese diet (Timsina and Connor, 2001; Timsina et al., 2010; Siddique and Li, 2019). However, the average yields of rice, maize, and wheat in Nepal are 26, 68, and 12% and 10, 14 and 18% lower compared to the neighbouring countries - Bangladesh and India, respectively (FAOSTAT, 2020). Non-availability of farm specific recommendations and reluctances to use general recommended rates of fertilizer by majority of the farmers are key factors for the high yield gaps of these cereals. Fertilizer recommendation methods based on soil analysis are relatively slow and expensive, and have failed to promote credible and actionable cereal nutrient management protocols for Nepal (Pandey et al., 2018). SSNM or NE-based nutrient recommendation, a plant-based approach (i.e., nutrient requirements based on yield target and NUE) as against soil-based approach, could be more efficient and robust method of nutrient recommendation for smallholder farmers of the EIGP of South Asia. Such approach has been widely evaluated and applied in cereal production systems in smallholder context in South and Southeast Asia (Witt et al., 1999; Dobermann et al., 2002; Dobermann, 2007; Buresh et al., 2010; Pampolino et al., 2012a, 2012b). Deploying a fertilizer recommendation strategy that is scientifically robust and inexpensive, and bypasses the requirement of soil testing may help implement and scale out SSNM protocols to improve cereal yields in Nepal and other countries in the EIGP with similar agro-climatic and soil conditions. Thus, the objectives of this study are i) to evaluate the NE-based nutrient recommendations for improving yield, economics, and NUE for rice, wheat, and maize; ii) to estimate climatic potential, attainable and actual farmers' yields of these crops and explore possibility for closing yield gaps with use of NE-based recommendation; and iii) to understand the key determinants for cereal yields and economic returns using the novel approaches of ML.

2. Materials and methods

2.1. Sites and climate characteristics

Six hundred farmer-participatory on-farm trials with rice, wheat and maize were conducted during 2014–2016 in four villages of two districts in Eastern Nepal located in the EIGP: Damak and Gauradaha villages in Jhapa district; and Itahara and Babiya Birta villages in Morang district (Fig. 1**; Supplementary Tables 1–3**). These districts have a sub-tropical climate with latitude and longitude ranging from 26.53^0 to 26.67^0 N and 87.43^0 to 87.72^0 E, respectively. Babiya Birta had a slightly different climatic pattern with annual rainfall of 2007 mm, maximum and minimum temperatures of 29^0C and 18^0C, respectively, and solar radiation of 18 MJ m^2 day^{-1}. On the other hand, Damak, Itahara and Gauradaha, had similar pattern with higher rainfall (2491 mm), maximum and minimum temperatures of 28 °C and 18 °C, respectively, and solar radiation of 18 MJ m^2 day^{-1} (**Supplementary Figs. 1, 2**). The villages in Morang and Gauradaha in Jhapa have all plain lands with Eutric gleysols soil; Damak in Jhapa, on the other hand, has plain lands with low gradient slope and Calcaric and Haplic Phaeozem soils. The landforms of all four villages have fluvial, non-calcareous parent materials (Dijkshoorn and Huting, 2009).

2.2. Description of on-farm trials

The on-farm trials were conducted during winter (Rabi; November to April) and monsoon (Kharif; July to October) seasons for four consecutive seasons (November 2014–October 2016). Trials were fully managed by participating farmers with close supervision and necessary supports were provided by researchers. In all the villages, rice-maize (R-M) and rice-wheat (R-W) are the predominant cropping systems. On-farm trials for each crop consisted of three treatments: i) T1: Farmer's fertilizer practice (FP, based on fertilizer application in their adjacent plots); ii) T2: Fertilizer application as recommended by Nutrient Expert (NE, based on farmer's responses to various questions; see **Supplementary Table 4a,b,c**); and iii) T3: Fertilizer application based on government recommendation (GR; $N:P_2O_5:K_2O$ @60:30:30 kg ha^{-1} for maize, @100:50:25 kg ha^{-1} for wheat, and @100:30:30 kg ha^{-1} for rice). The NE and FP treatments were implemented in both years with all farmers but the GR was in the first year only as the farmers preferred to apply NE-based recommendation only from the second year onwards. Fertilizer rates and splits across crops, treatments, fields, and years are shown in Supplementary Tables 1–3. In both years, the plot size for each treatment was 100 m^2 for rice and wheat and 150 m^2 for maize, and treatments in each field were randomly allocated following the principle of randomized complete block design.

In these trials, each farmer's field (set of three plots) was considered as a replication. Crop management practices (sowing/transplanting dates, variety, irrigation, pest and diseases, etc.) were homogeneous within the farmers' plots and may/may not differ across replications. It was our observation that the crop management practices were almost similar across farmers of same districts. Therefore, it could be considered with confidence that the only variation across replications were mainly nutrient management practices towards driving variations in observations.

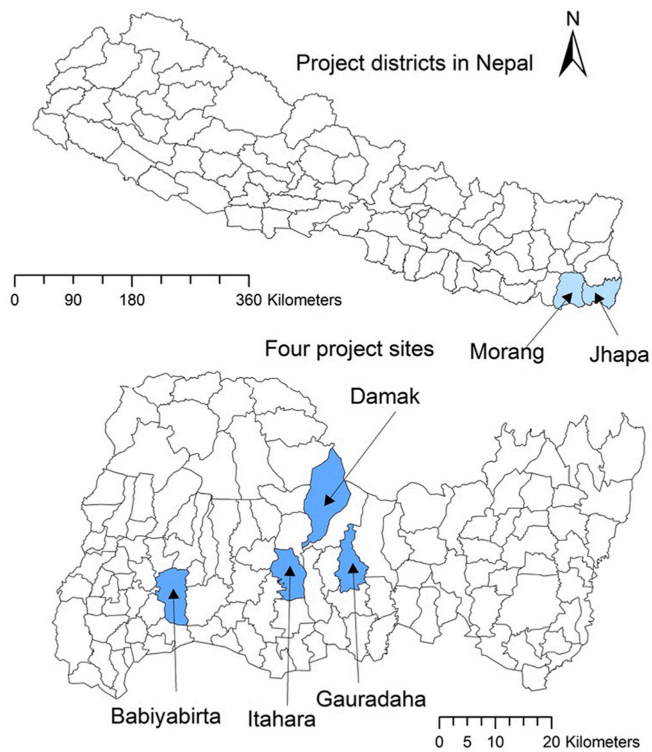

Fig. 1. Map showing two on-farm trials districts (Morang and Jhapa) and four project villages (Damak, Gauradaha, Babiyabirta and Itahara) in the EIGP of Nepal.

2.3. Crop management

For all crops and treatments, land preparation and crop establishment followed current farmers' practices. Sowing dates of wheat and maize and transplanting date of rice varied across years and locations depending upon the growing conditions. Rice transplanting date and wheat and maize sowing dates varied slightly in the villages within a district but varied more between the districts. Wheat and maize were sown during the first week of November to the last week of December and rice was transplanted during July and August. High yielding varieties, i.e., NL-297 for wheat, "Pioneer hybrid" for maize, and Ranjit, Swarna Sub-1 and Radha-12 for rice were used in each year depending on farmer's preference in each village. Seed rates for rice, wheat and maize were 30, 120, and 20 kg ha^{-1}, respectively, based on the recommendation from the District Agriculture Development Offices.

Water management in each crop and location followed local farmers' practice. Supplementary irrigations were provided in locations and years with insufficient rainfall, especially for wheat and maize, to avoid yield penalty due to moisture stress. In general, rice was grown as a rainfed in both districts, as eastern Nepal receives sufficient and well-timed rainfall during the monsoon season (NASA POWER, 2020). Across trials and years, rice received 0–3 supplementary irrigation while wheat and maize received 0–4. There were no major pest or disease outbreaks during the study period; the few sporadic incidences were well controlled by government recommended practices.

2.4. Yield and nutrient uptake estimation

Grain and straw/stover yields were collected from the central 20 m^2 sampling area of the plot at harvest. Samples were fully sun-dried to bring to an appropriate grain moisture content (14.5% for maize; 14% for rice and wheat) and 0–3% straw moisture content for all crops. Grain yields were recorded on a stable air-dry weight basis. Grain and stover samples were processed and analysed using standard methods to estimate nutrient uptake.

2.5. Nutrient Expert® and machine learning approaches

2.5.1. Nutrient Expert for rice, maize and wheat

Nutrient Expert® (NE; http://software.ipni.net/article/nutrient-expert), a computer-based nutrient decision support system (DSS), developed by the International Plant Nutrition Institute (IPNI) and its partners, works on the principles of SSNM. NE is an easy-to-use interactive tool tailored to a specific field or growing environment to assist farm advisors, extension agents and industry agronomists and provide fertilizer recommendation for an individual farmer's field in the presence or absence of soil test data (Pampolino et al., 2007, 2012b; Xu et al., 2014; Dutta et al., 2020). NE utilizes information on farmers' crop and soil management practices and growing conditions to provide a nutrient management plan (Supplementary Table 4a,b,c). NE recommendations are tailored to specific local conditions for crop yield, growth duration of the variety, crop residue management, past fertilizer use, and nutrient inputs from external sources. The details of principles, development, calibration and validation of NE- Rice, Wheat and Maize are well described in different peer reviewed articles (Pampolino et al., 2012a; Majumdar et al., 2016; Dutta et al., 2020; Rurinda et al., 2020).

2.5.2. Random Forest

Different biophysical and economic parameters were used in an ensemble learning technique, Random Forest (RF), to predict the grain yield of rice, maize, and wheat (Breiman, 2001; Devkota et al., 2021; Dutta et al., 2020). The RF algorithm has become attractive in several applications since it can handle high dimensional data ($n << p$) (Boulesteix et al., 2012). It does not depend on a specific stochastic model and can also capture nonlinear association patterns between predictors and target. Research has established that the RF ensemble with several trees leads to better prediction than an individual tree as used in CART (Krupnik et al., 2015b; Dutta et al., 2020). The RF algorithm combines numerous prediction trees where each tree is built from a bootstrap sample drawn from the calibration set. Notably, at each node of the tree the candidate set of the predictor is a random subset (mtry) of all the predictors. The final prediction of a new observation is calculated as the average of the predictions from all trees in the forest. In this study, the 'randomforest' package in R was used to execute the RF model with 500 trees. The prediction accuracy was determined using the coefficient of determination (R^2) (Williams, 1987). The missing values in the dataset were imputed by using the k-nearest neighbor (kNN) method. For executing the RF model, instead of splitting the data into calibration and validation sets, the Out-of-Bag (OOB) prediction, which is similar to cross-validation, was employed. A total of nine models [3 crops × 3 treatments] were created using the RF algorithm. For NE and FP, data from both years were combined while for GR, only first year data was used. Variables used as predictors for grain yields of all crops were cobs m^{-2} (for maize), straw yield, RoI, PFP of N, grain N uptake, total N uptake, IE and PNB of N, PFP of P_2O_5, grain P uptake, total P uptake, IE and PNB of P, PFP of K_2O, grain K uptake, total K uptake, and IE and PNB of K.

2.5.3. Simulation of climatic potential yield and the effect of seeding dates

Agricultural Production Systems SIMulator (APSIM) cropping Systems Simulation model, Version 7.10, (Holzworth et al., 2014) was used to estimate the climatic potential yield of rice, wheat, and maize for two situations. APSIM is widely used cropping-system modelling framework with robust rice, wheat and maize models, which simulate growth and yield of these crops with high accuracy. Especially in the context of Nepal, as of now there is more work in application of the DSSAT model (Jones et al., 2003). For the reliability of model results with precision, model inter-comparison is helpful. In future, we would like to see more model inter-comparison results. This study with APSIM application would offer some benchmarking for future APSIM applicators in Nepal and the EIGP. In this study, we first simulated potential yield for the fixed seeding dates (average dates used in on-farm trials), and then for seeding dates at 10-days interval from 1 January to 30 December for rice and maize, and from 1 October to 30 January (also at 10-days interval) for wheat. For the simulations, we used long-term climatic data from 1984 to 2018 using rainfall data of CHRIPS (Funk et al., 2015) and temperature, solar radiation and wind speed data from NASA POWER (2020). Simulations were made for two clusters based on similarity in climate data (one for Babiya Birta, and another for other three villages). For the multiple seeding dates, simulations were carried out only for Babiya Birta.

Pioneer Hybrid with sowing date (10 December) and physiological maturity (15 May); wheat variety NL-297 with sowing date (10 December) and physiological maturity (15 April), and rice variety Sona Masuri with transplanting date (25 July), seedling age (30 days) and physiological maturity (25 November) were used for yield prediction. The genetic coefficients for the rice variety were derived from ORYZA3 (Bouman et al., 2001; CSISA, 2017), while for maize, coefficients were adopted from Devkota et al. (Devkota et al., 2015; Devkota et al., 2016) based on CERES Maize under DSSAT (Jones et al., 2003). The coefficients of maize variety were then converted into APSIM using the procedure as recommended by the Agricultural Model Inter-comparison and Improvement Project (AGMiP). For wheat, the genetic coefficients of NL-297 calibrated earlier by the National Wheat Research Program (NWRP), Bhairahawa, western Nepal using DSSAT during 2012–2013 were converted into APSIM (Jones et al., 2003; Marahatta et al., 2018). For all crops, phenological development and grain yield were validated with the measured dataset.

2.6. Nutrient-use efficiency

2.6.1. Partial nutrient balance

Partial nutrient balance (PNB; Kg nutrient uptake kg^{-1} nutrient applied) is the simplest form of NUE and is expressed as nutrient output per unit of nutrient input (Dobermann, 2007; Fixen et al., 2015). PNB of a nutrient (N, P, K) was calculated as follows:

$$PNB-F=\frac{U(H)}{F} \quad (1)$$

where U(H) = nutrient content of harvested portion of the crop (or nutrient uptake); F = amount of applied nutrient (N, P, or K).

2.6.2. Partial factor productivity

Partial factor productivity (PFP; Kg grain kg^{-1} nutrient applied) of a given fertilizer is a simple production efficiency expression, calculated in units of crop yield per unit of nutrient applied. It more closely reflects the direct production impact of an applied fertilizer and relates directly to economic return (grain yield). PFP was calculated as follows:

$$PFP_x=\frac{\text{Grain yield}_x}{\text{Applied fertilizer x}} \quad (2)$$

where x is fertilizer N, P or K.

2.6.3. Internal utilization efficiency

Internal utilization efficiency (IE; Kg grain kg^{-1} nutrient uptake) for each nutrient under different nutrient management practices was calculated based on Dobermann (2007) and Fixen et al. (2015).

$$IE_x=\frac{\text{Grain yield}}{\text{Nutrient (x) uptake by aboveground plant}} \quad (3)$$

where “x” refers to N, P or K.

2.7. Economic analysis

A complete inventory of all fertilizer inputs and outputs (grain and stover) was prepared and the cost of fertilizers and net profit (Nepalese Rupees, Rs ha^{-1}) for each nutrient management treatment in each district were computed. Total fertilizer cost was recorded for all fertilizers from all farmers of all villages in each district during each crop season, while output prices (sale of grain and straw/stover) were obtained through surveys conducted at the end of the season, with additional market prices garnered from the nearest market to trial locations to triangulate results. Fertilizer input and grain and straw output prices did not vary by >5% within a district or year and were therefore averaged for two years. The costs and returns were used to calculate the gross returns and return on investment in fertilizer (ROI) and to determine the net economic impacts associated with alternative fertilizer management practices. The average prices for urea and diammonium phosphate was Rs 22 and 50 kg^{-1} respectively while the price of muriate of potash varied between Rs 30 and 40 kg^{-1} among seasons or crops. The average grain prices for rice, wheat and maize were Rs 23.6, 25 and 18 respectively while those for straw were Rs 3.0, 1.0 and 3.0 kg^{-1} respectively [Exchange rate: US$ 1 = 120 Rs].

ROI (Rs Rs^{-1}) was calculated as follows:

$$ROI=\frac{\textit{Gross return}}{\textit{Total cost of fertilizer}} \quad (4)$$

2.8. Statistical analysis and visualization

2.8.1. Statistical analysis

Before performing the statistical analysis, the normality assumption of analysis of variance (ANOVA) was tested following Snedechor and Snedecor and Cochran (1989). Since this assumption was met, there was no need for data transformation. As the design was with unbalanced replications, a linear mixed effect (LME) model for ANOVA using the ‘lme4’ package (Bates et al., 2015) considering nutrient management (treatments) and locations (villages) as fixed effects and year as random effect within R statistical package (version 3.6.2) (R Core Team, 2020) was used. LME models are an augmentation of simple linear models to permit both fixed and random effects and are mostly applied when there is non-independence in the data, such as develops from a hierarchical structure. Further, across treatments and locations, pairwise difference comparisons were made based on Tukey’s HSD test (95%).

2.8.2. Data visualization

For data visualization, mainly the box and whisker plots and cumulative distribution function (CDFs) were used. Box and whisker plots including minimum, maximum, mean, median and interquartile range were constructed to examine the variability in cereal yields and ROI across trials. Descending CDFs for each crop under each nutrient management practice were constructed using the individual data of all treatments over two years. CDFs describe the potential of obtaining the grain yield or ROI greater than a given probability level (0–100%) using data from each farmer from all districts. A no-risk, high yield or high ROI scenario can be shown as a vertical-leaning line placed as far to the right as possible on the abscissa; this approach has also been used by other workers in the EIGP (e.g., Gathala et al., 2016; Islam et al., 2019).

3. Results and discussion

3.1. Nutrient management practices on yield and economics

Nutrient management practices had a significant ($p < 0.05$) effect on yield and profits of all crops across the study locations (Fig. 2; Table 1). Averaged across the locations, the NE-based recommendation performed better in terms of yield and gross return for all crops over both FP and GR. Averaged across locations, NE had 3.5 t ha^{-1} higher maize yield and 1.0 and 1.3 t ha^{-1} respectively higher wheat and rice yields over FP, indicating that the yield gaps in all cereals was due to inefficient fertilizer management. Yield improvement was also observed in NE over GR by about 2.5, 0.6, and 1.0 t ha^{-1} for maize, wheat and rice, respectively (Table 1). While comparing the overall economic performance of the nutrient management practices, the gross return also showed similar patterns as with yield (Fig. 2, Table 1). The spatial distribution also highlighted the significant differences ($p < 0.05$) in ROI across the villages and districts. Data indicate that in all cereals, the yield gaps between NE and the other two treatments across locations were due to inappropriate management of fertilizers.

Based on the LME models’ results (Table 1; Supplementary Table 5), both the treatment and location effects for grain yield were highly significant in all three crops, implying that at least two groups had different means. The familywise error rate was controlled at the $p = 0.05$ level. The Tukey’s HSD showed the pairwise differences among three treatment groups for each crop (Table 1). For grain yields of all crops, the point estimate of the difference was highest for NE-FP and lowest for GR-FP. Conversely, for ROI, PFP-N and PFP-P_2O_5, no consistent trends were observed, although some similarities were observed for rice and wheat. Notably, the confidence interval (CI) for all tested parameters for most of the groups in all three crops exhibited significant differences between the two treatments. For maize and rice, the point estimates and CI, as shown by the Tukey’s HSD for pairwise comparison between two districts for all five parameters, exhibited significant differences in most cases. However, for wheat, only 14 out of 30 parameter-village combinations exhibited significant differences (Supplementary Table 5).

The spatially distributed grain yield and ROI, as shown in the box and whisker plots (Fig. 2; **Supplementary Figs. 3 and 4**), also revealed that NE-based recommendation outperformed other fertilizer management practices for grain yield in all locations and crops. The comparison between treatments showed that while keeping other management practices same, changes in nutrient management alone could make significant positive impact on yield. Previous studies also suggested that nutrient management plays significant role in improving yield and economics (Dobermann, 2007; Dobermann et al., 2002; Dobermann, 2007). For example, NE based recommendations increased rice grain yield of about 2 t ha^{-1} over FP across different locations of Nepal (Amgain et al., 2021). In another study, Xu et al. (2014) reported that compared to FP, the NE recommendation increased maize grain yield by

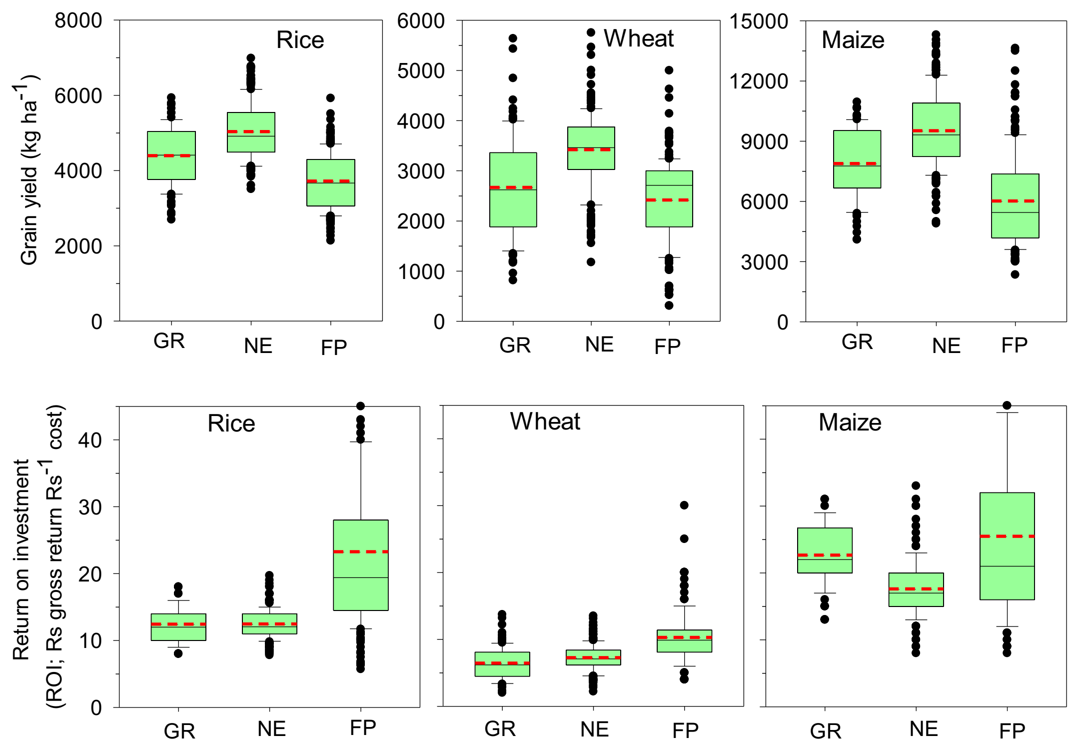

Fig. 2. Grain yield (*Upper row*) and return on investment (*lower row*) from rice, wheat and maize under three different nutrient management practices. Data combined over two years and four on-farm trial sites from the EIGP of Nepal. Solid black line inside the box is the median and the dotted red line is the mean.

upto 0.6 t ha^{-1} in six provinces of China. Pampolino et al. (2012b) also reported an average of 0.9 t ha^{-1} and 0.3 t ha^{-1} wheat grain yield improvements over FP and State recommendations respectively in more than 100 study locations across South Asia. In all these cases, NE recommendations improved the yield as well as gross return.

While calculating the fertilizer rates and generating the recommendations, NE considers the farmers' field management history, attainable yield target, soil inherent nutrient supplying capacity, plant internal nutrient efficiencies and water availability. Once the NE estimates the fertilizer amounts, it then suggests the right fertilizer source and right time to apply them considering the water availability and plant growth stages (Pampolino et al., 2012a; IPNI, 2017).

3.2. Nutrient management practices and internal efficiency

The average internal efficiency (IE) of the three major nutrients in all the cereal crops (except for P and K in maize) varied across nutrient management strategies (Table 2; **Supplementary Fig. 5**). Higher IE-N was observed for NE in rice and for GR in wheat and maize, and lower IE-N for FP in all crops. The IE of N, P, and K showed significant clustering of points for rice while for wheat and maize the variability was high (Supplementary Fig. 5). The IE can be optimized with the yield target based on NE, i.e., 5 t ha^{-1} for rice, 3.4 t ha^{-1} of wheat and 9.5 t ha^{-1} for maize. Low and varying IEs in FP were most likely caused by nutritional imbalances. The low IE values with low yields in FP for all three crops and nutrients indicated opportunities for significant improvement. An extremely high IE of a nutrient suggests deficiency of that nutrient while a low IE suggests poor internal nutrient conversion due to other stresses such as deficiencies of other nutrients, drought or heat stress, mineral toxicities, pest damage, etc. (Witt et al., 1999).

There are considerable uncertainties about N, P and K requirements by crops as the IE varies greatly depending on variety, nutrient supply, crop management and climatic conditions (Van Duivenbooden et al., 1996). The IE of all three cereals in the current study differed from IE obtained in many of the earlier studies. Those studies have reported variations in N, P, K requirements due to variations in IE; for example, in rice (Dobermann et al., 1996; Witt et al., 1999; Buresh et al., 2010), wheat (Pathak et al., 2003; Chuan et al., 2013), and maize (Setiyono et al., 2010). The differences in IEs between these studies and our study were mainly due to (i) use of a newer commercial maize hybrid at the sites in our study and (ii) generally higher yield levels and less abiotic stresses in our trials with sufficient availability of water. Our findings suggest that the future challenge in efficient and sustainable nutrient management will be to increase the IEs in farmers' fields at constant or increased grain yield levels by a balanced N, P and K nutrition and improved crop management.

3.3. Nutrient management practices and partial nutrient balance

The PNB of N, P and K (kg nutrient removed kg^{-1} nutrient applied) differed among nutrient management options and crops (Table 2; Fig. 3). Average PNBs of N, P, and K across treatments in rice were 1.29, 1.53 and 5.82; in wheat were 0.79, 0.81 and 2.48, and in maize were 2.63, 2.58 and 6.43, respectively. Wheat had the lowest average PNBs of N (<1.0), P (<1.0) and K (<2.0) followed by rice ($N < 1.5$, $P < 2.0$ and K < 6.0), while maize had the highest PNB of all nutrients ($N > 1.5$, $P > 1.5$ and $K > 6.0$). FP had significantly higher PNB of all nutrients in rice and wheat and of K in maize. Very high PNB-K in FP was due to fewer numbers of farmers applying K fertilizer, where only 17% farmers in rice, 32% in wheat, and 33% in maize applied K fertilizer. Liu et al. (2011) found large differences in PNB of N, P and K for wheat for three regions of China due to differences in climate, soil properties and cropping systems, with average PNB of 0.73, 0.81 and 0.60, respectively, across regions.

The PNB analysis offered a baseline and target values for yield and PNB for major cereal crops in Nepal. The primary goal of the measure of PNB is to determine how close a system is to PNB of 1. Typical PNB values for rice, wheat and maize range from 0.7 to 0.9 for all three nutrients (Fixen et al., 2015). Our study revealed PNB values closer to 1 for GR and NE in rice. High PNB values for N, P and K for maize across

Table 1
Pairwise difference comparisons of grain yield, ROI and PFP of nutrients based on Tukey's HSD test (95%) for three nutrient management treatments in the EIGP of Nepal.

Pairwise computation	Maize					Rice					Wheat				
Treatments	Grain yield (t ha^{-1})	ROI	PFP-N	PFP-P_2O_5	PFP-K_2O	Grain yield (t ha^{-1})	ROI	PFP-N	PFP-P_2O_5	PFP-K_2O	Grain yield (t ha^{-1})	ROI	PFP-N	PFP-P_2O_5	PFP-K_2O
GR-FP	1 (0.4, 1.9)*	−7 (−10, −4)*	20 (10,30)*	2 (−30, 40)	−150 (−190, −80)*	0.5 (0.2, 0.6)*	−15 (−18, −12)*	−40 (−50, −30)*	−50 (−70, −20)*	–	0.5 (0.2, 0.8)*	−3.5 (−5, −2.5)*	−10 (−15, −7)*	−20 (−30, −10)*	–
NE-FP	3.5 (3, 4)*	−8 (−10, −6)*	−15(−25, −5)*	38 (2, 58)*	−140 (−180, −100)*	1.3 (1.2, 1.5)*	−10 (−12, −18)*	−20 (−25,-15)*	−10 (−20,10)	–	1.0(0.8, 1.2)*	−3 (−3.5, −2)*	−5 (−8, −3)*	−2 (−10, 5)	–
NE-GR	2.5 (1.7, 3)*	−1 (−4, 2)	−35 (−50, −20)*	25 (−5, 60)	2 (−40, 45)	1 (0.8, 1.2)*	5 (2, 7)*	20 (10,30)*	40 (20, 60)*	−14 (−21, −6)*	0.6 (0.3, 0.8)*	1 (−0.5, 2)	5 (3,10)*	20 (10, 30)*	−50 (−70, −35)*

The values outside the parentheses indicate the point estimates of the difference between two nutrient management treatments and those inside indicate confidence intervals.

treatments indicate inadequate external supply of nutrients that may affect future sustainability of production. In rice and wheat, the highest PNB values for all three nutrients was observed with FP, but the yield was lower by 32 and 46% in rice and 10 and 41% in wheat, respectively compared to GR and NE. The combination of high PNB values and low yields are also not desired, as it indicates soil nutrient mining and might not be sustainable in long-run. The high yields with NE and consistent PNB of all nutrients indicated that the NE-based nutrient recommendation might offer the entry point for future yield improvements though there are still opportunities to optimize rates to bring down PNB below 1.0 for all nutrients in maize and for K in rice and wheat.

However, the PNB calculation is a partial balance, and using a PNB of 1 as an indicator of soil fertility sustainability can be misleading, particularly in regions with low indigenous soil fertility and low inputs and production. In contrast, a PNB of well below 1 indicates nutrient inputs far exceeding nutrient removal, suggesting avoidable nutrient losses and thus the need for improved nutrient management (Snyder and Bruulsema, 2007). A PNB greater than 1 means more nutrients are removed with the harvested crop than applied by fertilizer and/or manure, or nutrients might have been added from soil mineralization, leading to "soil mining" of nutrients. The latter situation may be desired if available nutrient contents in the soil are known to be higher than recommended. However, in cases where soil nutrient contents are at or below recommended levels, a PNB >1 could be regarded as unsustainable (Brentrup and Pallière, 2010). Fixen et al. (2015) reported that PNB above 0.94 can result in declining soil P levels with substantial declines with the most negative P balance. We hypothesize that long-term measurement of PNB would be a good indicator for long-term soil P fertility on non-P fixing, but not on P-fixing, soils. Since over the short term and on individual farms, PNB can show substantial fluctuations, especially for P and K, we recommend for long-term assessment of PNB in the EIGP.

3.4. Nutrient management practices and partial factor productivity

The PFP of nutrients is the measure of grain yield in relation to nutrient applied; optimal values of PFP for all three nutrients in all crops are desired for the sustainability of crop production. In this study, the PFP of N, P_2O_5 and K_2O differed across nutrient management methods and crops (Table 2; Fig. 4). The average PFPs of N, P_2O_5 and K_2O in rice were 52, 168 and 173; in wheat were 32, 70 and 118; and in maize were 103, 269 and 272 kg grain kg^{-1} N, P_2O_5 and K_2O applied respectively (Table 2). In rice and wheat, the highest PFP of all three nutrients was observed in FP while in maize the highest PFP of N, P_2O_5 and K_2O was in GR, NE, and FP respectively (Fig. 4). Interestingly, while the performance of NE in terms of PFP-N was poorer over FP and GR in maize, its performance was better over GR in both rice and wheat (Table 1).

This study has also established the relationship between yield and PFP for all three nutrients and established the baseline values for the yield targets. It shows that the PFP-N of 40–60, PFP- P_2O_5 of 150–200 and PFP- K_2O of 100–150 kg grain kg^{-1} nutrient applied would be optimal with higher yield for rice; slightly smaller values in wheat and slightly higher in maize than in rice could be achieved with yield targets of more than 6 t ha^{-1} for rice, >5 t ha^{-1} for wheat and > 10 t ha^{-1} for maize. However, the PFP-N values of higher than 100, 50 and 150 respectively for rice, wheat and maize with yield targets of FP (3.7, 2.4 and 6.0 t ha^{-1} respectively) could cause soil nutrient mining. In FP, nutrient application was low; as stated earlier many farmers applied lower K rates to these crops (Supplementary Tables 1–3), which resulted in higher PFP than the optimum threshold recommended by EU (E. U. Nitrogen Expert Panel, 2015). The PF*P* values showed that in FP, farmers are applying sub-optimal amounts of fertilizers and hence the farmers participating in on-farm trials in all three crops are causing nutrient mining. On the other hand, PFP values for NE and GR methods of nutrient application were stable or increased with increasing yield, indicating the possibility of high PFP with increasing yield and sustainability of cereal cropping in terms of use efficiencies of N, P and K.

Table 2
Analysis of variance (ANOVA) showing internal efficiency (IE), partial factor productivity (PFP) and partial nutrient balance (PNB) of nutrients as affected by three nutrient management practices in rice, wheat and maize in the EIGP of Nepal.

Nutrient management	Rice			Wheat			Maize		
Internal efficiency (IE)									
	IE-N	IE-P	IE-K	IE-N	IE-P	IE-K	IE-N	IE-P	IE-K
FP	40b	246b	34b	40c	194c	54c	63b	248b	108b
GR	40b	247b	35b	43a	210a	69a	75a	247b	134a
NE	43a	258a	40a	41b	201b	58b	58b	256a	127a
P value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.34	Ns
Partial nutrient balance (PNB)									
	PNB-N	PNB-P	PNB-K	PNB-N	PNB-P	PNB-K	PNB-N	PNB-P	PNB-K
FP	1.75a	1.66a	10.15	0.96a	0.99a	3.93a	2.47b	2.47a	8.25a
GR	1.07b	1.40b	4.14	0.63c	0.58b	2.01b	3.36a	2.56a	6.01b
NE	1.04b	1.53ab	3.17	0.79b	0.87a	1.49c	2.06c	2.71a	5.03c
P value	<0.001	0.004	<0.001	<0.001	<0.001	<0.001	<0.001	0.08	<0.001
Partial factor productivity (PFP)									
	PFP-N	PFP-P_2O_5	PFP-K_2O	PFP-N	PFP-P_2O_5	PFP-K_2O	PFP-N	PFP-P_2O_5	PFP-K_2O
FP	69a	180a	301a	38a	81a	178a	95b	261a	329a
GR	42b	151b	116b	27c	53b	107b	133a	266a	266b
NE	44b	173a	102b	32b	77a	69c	81c	281a	220c
P value	<0.001	0.007	<0.001	<0.001	<0.001	<0.001	<0.001	0.07	<0.001

The PFP ranges for all nutrients across the three cereals obtained in our study are much wider compared to the typical PFP values for rice, wheat and maize (40–90, 45–110 and 60–165 kg ha^{-1} for N, P_2O_5 and K_2O respectively) as reported by Fixen et al. (2015). Liu et al. (2011) also showed large differences in PFP in three regions of China, which was attributed to differences in climate, soil properties and cropping systems. Our results differ from Liu et al. (2011) who reported an average PFP for N, P_2O_5 and K_2O of 36, 143 and 72 kg grain kg^{-1} nutrient application, respectively for large number of wheat datasets analysed from across three regions in China. Our PFP-N values are generally lower for rice and wheat but higher for maize than those reported by Ladha et al. (2005) who, based on a literature review, reported the PFP-N of 62, 45 and 72 respectively for rice, wheat and maize. The increase in PFP of all nutrients and particularly for maize in recent years has resulted mostly from the improved genetics and crop, soil and nutrient management, which has boosted yields in all crops. Differences in PFP for N, P_2O_5 and K_2O across crops and nutrient management practices in our study and those of the above studies were attributed to variations in soil, climate, and management conditions.

3.5. *Effect of nutrient management practices on risks and variability of grain yield and ROI*

3.5.1. *Grain yield*

Comparing across the three nutrient management options, the cumulative density functions (CDFs) for grain yield of rice ranged from 3 to 7 t ha^{-1} (Fig. 5), with ranges for GR, NE and FP of 3 to 6, 4 to 7 and 3 to 5 t ha^{-1}, respectively. There were large differences in the probability of achieving a given rice yield across treatments, with NE always producing higher yield, but for GR and FP there were some overlapping yields. At the 50% probability level rice yield exceeded 5.3 t ha^{-1} in NE, 4.5 t ha^{-1} in GR, and 4.3 t ha^{-1} in FP. Further, there was only 5% probability of exceeding 5 t ha^{-1} in FP; this increased to 27% probability in GR and to 60% in NE.

In wheat, grain yield across treatments ranged from 0.3 to 5.6 t ha^{-1}, ranging from 1 to 5.4, 1.4 to 5.6 and 0.3 to 4.8 t ha^{-1} in GR, NE and FP, respectively (Fig. 5). There were much larger differences in the probability of achieving a given wheat yield across treatments than the rice yield, with NE had highest yield followed by GR and FP. At the 50% probability level wheat yield exceeded 3.4 t ha^{-1} in NE, 2.6 t ha^{-1} in GR, and 2.1 t ha^{-1} in FP. Further, there was only 4% probability of exceeding 4 t ha^{-1} in FP and 8% in GR while it was 23% in NE.

In maize, yield across treatments and years ranged from 4 to 14 t ha^{-1}; the corresponding ranges for FP, GR and NE were 3 to 13.5, 4 to 11, and 5 to 14 t ha^{-1}, respectively (Fig. 5). As in wheat, maize yields at all probability levels were highest for NE, followed by GR and then FP. At the 50% probability level maize yield exceeded 5 t ha^{-1} in FP, increasing to 8 t ha^{-1} in GR, and further to 9 t ha^{-1} in NE. Further, there was only 19% probability of exceeding 8 t ha^{-1} in FP, increasing to 44% probability in GR and to 78% in NE. In all three crops, the higher percentage for achieving higher yield with NE suggests that yield can be maximized and yield gap reduced through the adoption of NE-based fertilizer recommendation in the EIGP. Similar findings on yield improvement with better fertilizer management has been reported for Terai as well as mid-hill districts of Nepal and in Eastern India (Amgain et al., 2021; Dutta et al., 2020).

3.5.2. *Return on investment*

The ROI (Rs profit Rs^{-1} investment in fertilizer) from rice across the three nutrient management options ranged from 8 to 92 (Fig. 5). The corresponding ROI for GR, NE and FP was 8 to 18, 8 to 19 and 16 to 92 respectively. At 50% probability, ROI in rice was at least 29 in FP which decreased to 13 in GR and 14 in NE. However, at higher (90%) probability, the secure ROI decreased to 20 in FP, 9 in GR and 10 in NE. It indicates that for a farmer aiming at an ROI of 12, the probability of obtaining such ROI from rice was 100% in FP, which decreased to 84% in GR and 91% in NE.

The ROI from wheat was less (2 to 28) than that from rice, ranging from 2 to 13, 3 to 13, and 14 to 28 in GR, NE and FP, respectively (Fig. 5). At 50% probability, ROI from wheat exceeded 10 in FP and 6 each in GR and NE, and at 90% it decreased to 5, 3 and 4 respectively in FP, GR and NE. This suggests that if a farmer was aiming at receiving an ROI of 5 from wheat (lesser than that from rice), the probability of obtaining such ROI was 89% in FP, 72% in GR, and 77% in NE.

Maize is a high-yielding and highly-profitable crop and farmers can expect high economic returns from maize. The ROI from maize across the three nutrient management treatments and years ranged from 13 to 98, with 9 to 98 from FP, 13 to 31 from GR and 9 to 31 from NE (Fig. 5). At 50% probability, ROI exceeded 21 in FP, 20 in GR and 17 in NE. At 90% probability, ROI exceeded 12 in FP, 17 in GR and 13 in NE. This shows that if a maize farmer was aiming at receiving the ROI of 20 from maize (higher than that from rice or wheat), the probability of obtaining such a high ROI was 55% in FP, 70% in GR, and 53% in NE. These production and economic risks results suggest that though ROI in rice and wheat is higher with FP and in maize higher with GR, maize could be grown with NE-based recommendation due to low risk of obtaining high yield and moderate ROI. Similar findings on improvement in profits with better fertilizer management has been reported for Terai as well as

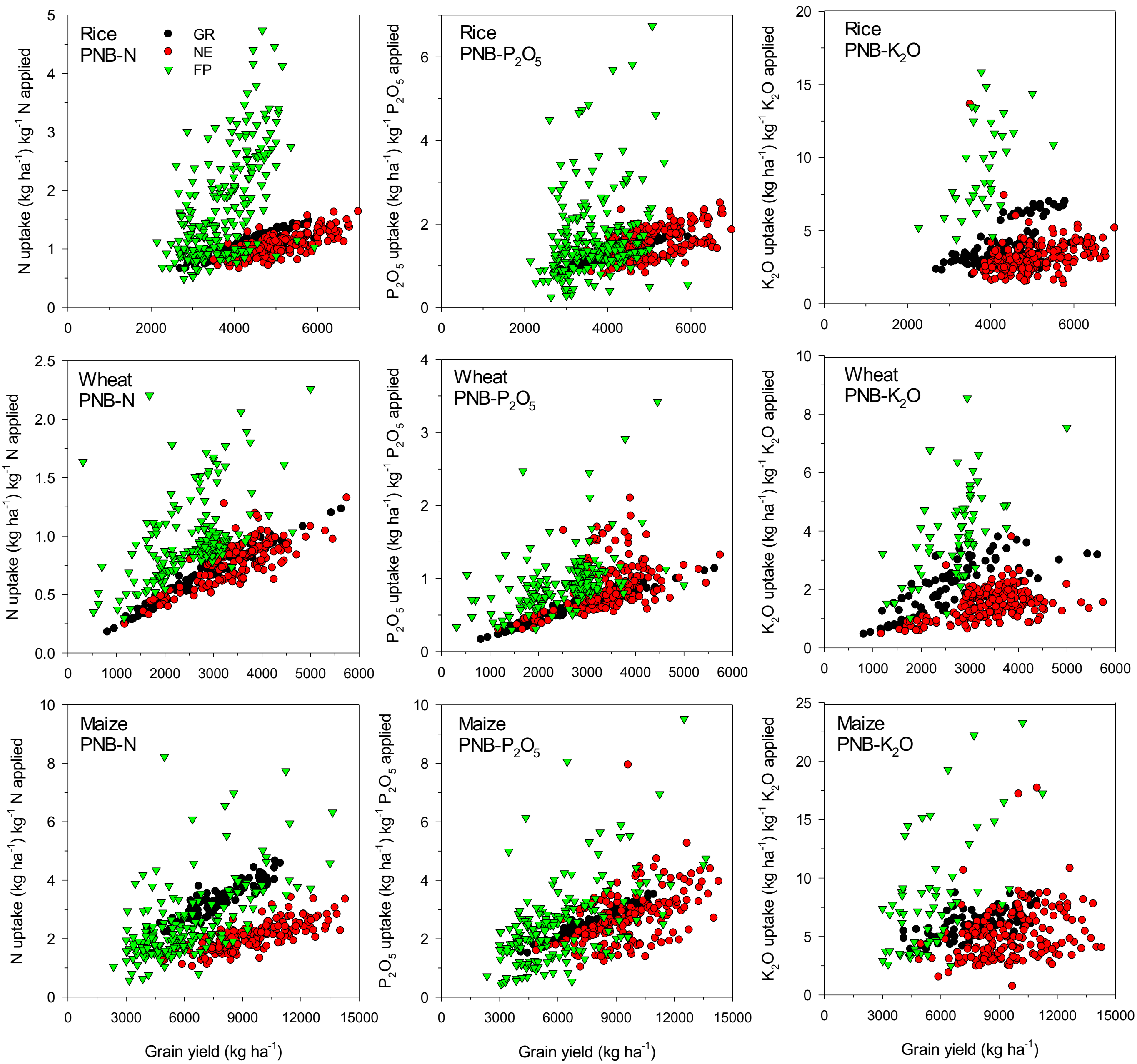

Fig. 3. Partial nutrient balance (PNB; kg nutrient uptake per kg nutrient applied) for N, P and K fertilizers in rice (top row), wheat (middle row) and maize (bottom row) crops under three different nutrient management practices. Data combined over two years and four on-farm trial sites from the EIGP of Nepal.

mid-hill districts of Nepal, Eastern India and sub-Saharan Africa (Dutta et al., 2020; Rurinda et al., 2020; Amgain et al., 2021). Amgain et al. (2021) reported around 20% increase in gross return with NE-based recommendation over FP and this increase was attributed to higher yield and less input cost.

3.6. Effect of climate and planting date on potential yield

The potential yield (PY) of any crop variety is its theoretical, climatically-derived yield, simulated under non-limiting conditions of water, nutrients, and pest and diseases and is governed by temperature and solar radiation (Bouman et al., 2001). The long-term yearly mean simulated PY of rice using climate data for 1985–2018 for 25th June transplanting date for the four villages in Eastern Nepal ranged from 7 to 7.5 t ha^{-1} while for the 10th December planted wheat and maize, it ranged from 5 to 5.5 and 13 to 13.3 t ha^{-1}, respectively (Fig. 6). Long-term PY simulations for transplanting of rice in Babiya Birta in 10-days interval from January to December showed that rice could be transplanted to receive high PY from mid-February to mid-September (Fig. 6B). Planting between 10th October and 30th December was too risky as PYs in many years were zero with yield variability of more than 30% due to cold injury. Under irrigated condition, optimal rice transplanting date ranged from 20th March to 20th April (which is also the farmers' preferred time for spring rice planting) and has the climatic PY of 7.6 t ha^{-1} with coefficient of variation of 17%. The second planting season is from 1st to 30th of July (which is also the farmers' preferred time for main monsoon season rice planting) and has the climatic PY of 7.2 t ha^{-1} with coefficient of variation of 20% (Fig. 6B). For maize, long-term PY across years in Babiya Birta ranged from 2 to 11 t ha^{-1} (mean: 8 t ha^{-1}) for planting on 10th July and from 11 to 15 t ha^{-1} (mean: 14 t ha^{-1}) for planting on 20th November (Fig. 6C). For the constant maize sowing date (10 December), long-term PY ranged from 11 to 15 t ha^{-1}

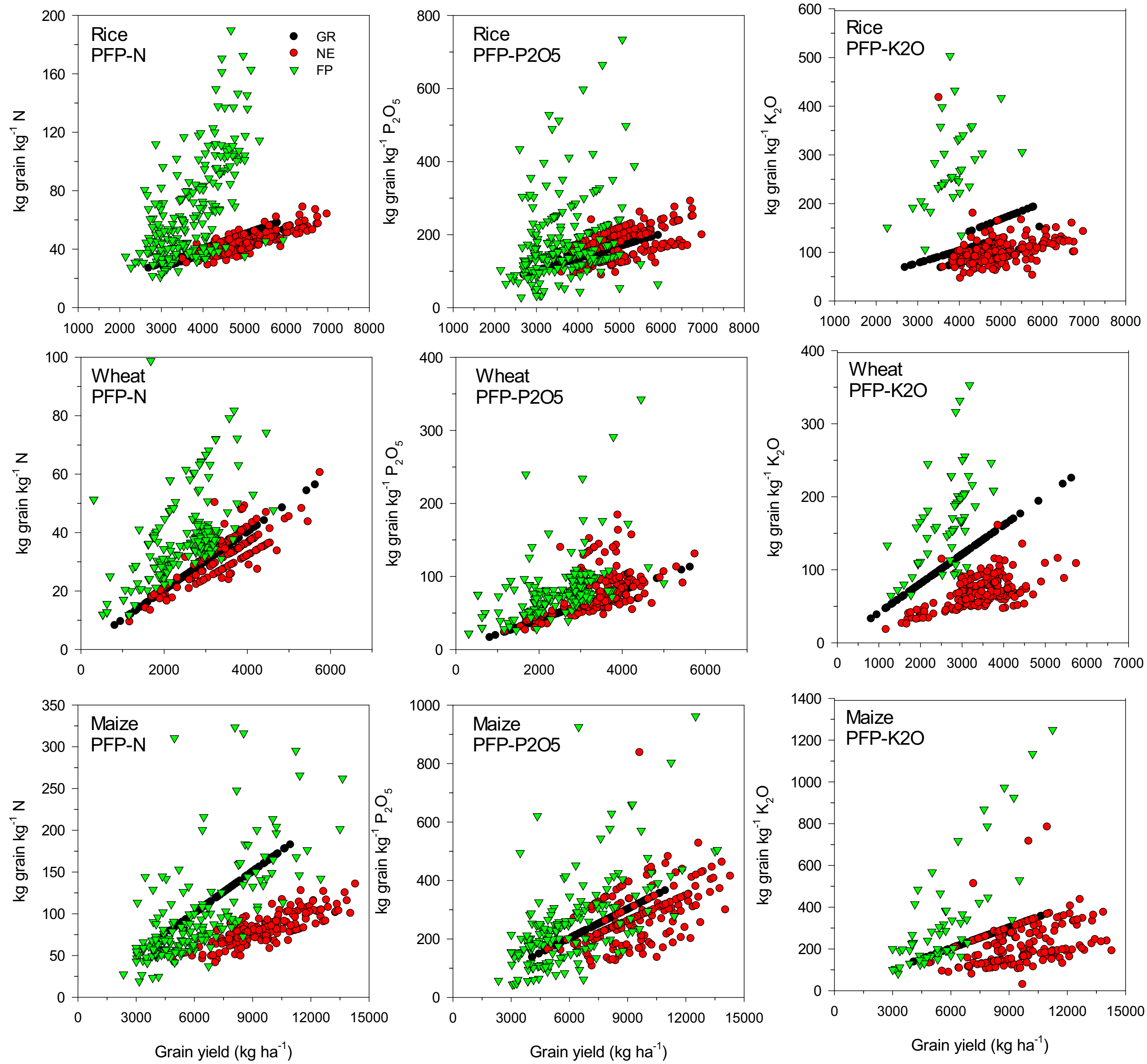

Fig. 4. Relationship between partial factor productivity (PFP; kg grain kg^{-1} nutrient applied) of N, P_2O_5 and K_2O and grain yield in rice (upper row), wheat (middle row), and maize (lower row) crops under three different nutrient management practices. Data combined over two years and four on-farm trial sites from the EIGP of Nepal.

and from 12 to 15 t ha^{-1} with mean yields of 13 t ha^{-1} in Babiya Birta and other sites respectively (Fig. 6A). For wheat, PYs were lower ranging from 4 to 6.5 t ha^{-1} and from 4 to 7 t ha^{-1} with mean yields of 5 t ha^{-1} in the two site groups respectively when planted on 10th December (Fig. 6A) and from 3.5 to 5.5 t ha^{-1} (mean: 4.4 t ha^{-1}) for 10th October planting and from 4 to 7 t ha^{-1} (mean: 5.5 t ha^{-1}) for 10th January planting (Fig. 6D).

Our results show small differences in PY of the three cereals across the four villages due to minor differences in climate. The higher simulated PY of rice in the three villages (Damak, Gauradaha and Itahara) compared to Babiya Birta might be due to higher amount of rainfall in those locations compared to Babiya Birta (Supplementary Fig. 2). Simulated attainable yield of maize of ~8 t ha^{-1} with 150 kg N ha^{-1} (Devkota et al., 2016) and attainable yield of rice of ~7 t ha^{-1} (CSISA, 2017; Devkota et al., 2021) in Terai region of Nepal further supports the possibility to increase yield of these crops in the EIGP. However, the rice, wheat and maize yields varied across years, locations, and planting dates indicating that the yield variability was due to rainfall amount and frequency, soil type and soil fertility, and other climatic variables (Cooper et al., 2008).

The simulated PYs of rice under varied climatic scenario are consistent with the ORYZA2000 simulation results by Timsina et al. (2010) who obtained PYs of various rice varieties differing in growth duration ranging from 2 to 14 t ha^{-1} when transplanted in monthly interval from 1 January to 1 December in Chitwan, Central Nepal Terai. Planting time might differ slightly due to maturity difference of the variety and tolerance to cold, as the first planting date (1 January) coincides with the nursery establishment during cold period (temperature < 20 °C). Our results for PY of maize are also consistent with Timsina et al. (2010) who also reported yield potential of maize hybrids of

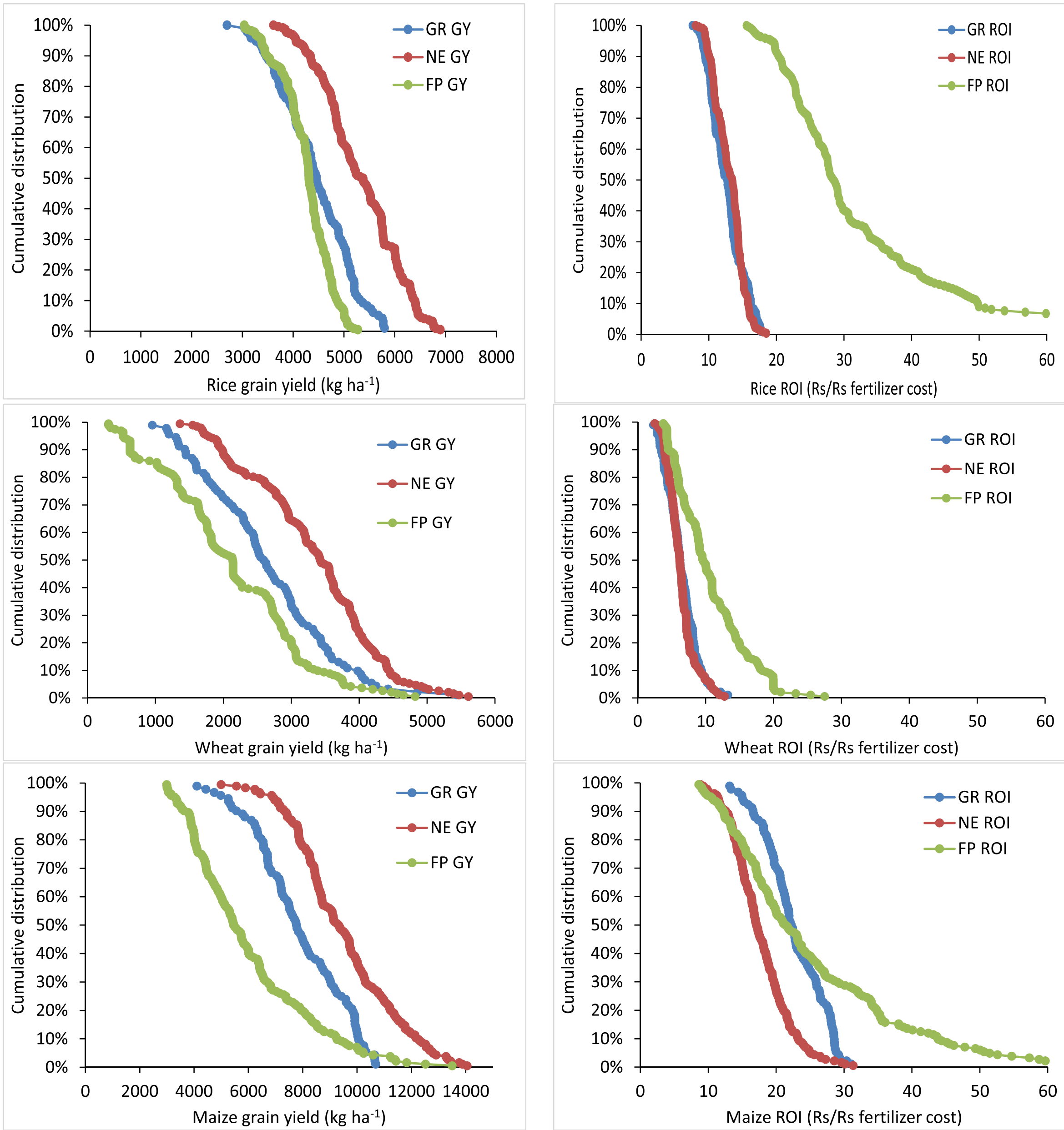

Fig. 5. Probability of exceedance for **grain yield** (*left column*) and **ROI** (*right column*) of rice, wheat and maize under three nutrient management practices in the EIGP of Nepal.

varying durations, estimated by the Hybrid Maize model, of upto 15 t ha^{-1} when maize was planted at various dates. In the EIGP of Nepal, with irrigation facility and without any nutrient limitations and pest and disease constraints, the winter maize has better resilience (low yield variability) for planting from mid-November to mid-January (Fig. 6C). Multi-location maize hybrid evaluation trials across the Nepal Terai region during the winter season also showed October–November planting had significantly higher yield with lower barren cob due to cold-induced sterility (Tripathi et al., 2016). In wheat, advancing or delaying sowing date requires additional N fertilizer rate and supplementary irrigation, respectively to safeguard yield by beating terminal heat stress (Krupnik et al., 2015a; Dubey et al., 2020). Thus, with irrigation facility and without any constraints, wheat can be planted from 10 November to 10 January with small coefficient of variation (11%) (Fig. 6D). Our study used APSIM (with DSSAT and ORYZA models embedded) for simulation of PYs of the three cereal crops. These models have been calibrated and validated well across Asia (Timsina and Humphreys, 2006; Sudhir-Yadav Li et al., 2011; Gaydon et al., 2017). However, aside from few studies, there has been no validation and application of these models in Nepal; hence the current study becomes novel in modelling yield potential of these major cereals in the EIGP of Nepal. However, we lacked data for growth and biomass of all crops for the model calibration and validation and the simulations were mostly based on yield at harvest and crop phenological development. Future research should aim for rigorous calibrations and validations of these models before their applications.

3.7. *Crop yield gaps across sites and years*

Mean on-farm trial yields of the three cereals across sites and years in FP and NE show low yield variability for both treatments (Table 3), due to close proximity of the sites and similar agro-climatic condition (Supplementary Figs. 1 and 2). There were larger yield gaps between PY and FP (YG1; 2.6–8.5 t ha^{-1}) than PY and NE (YG2; 2.0–3.7 t ha^{-1})

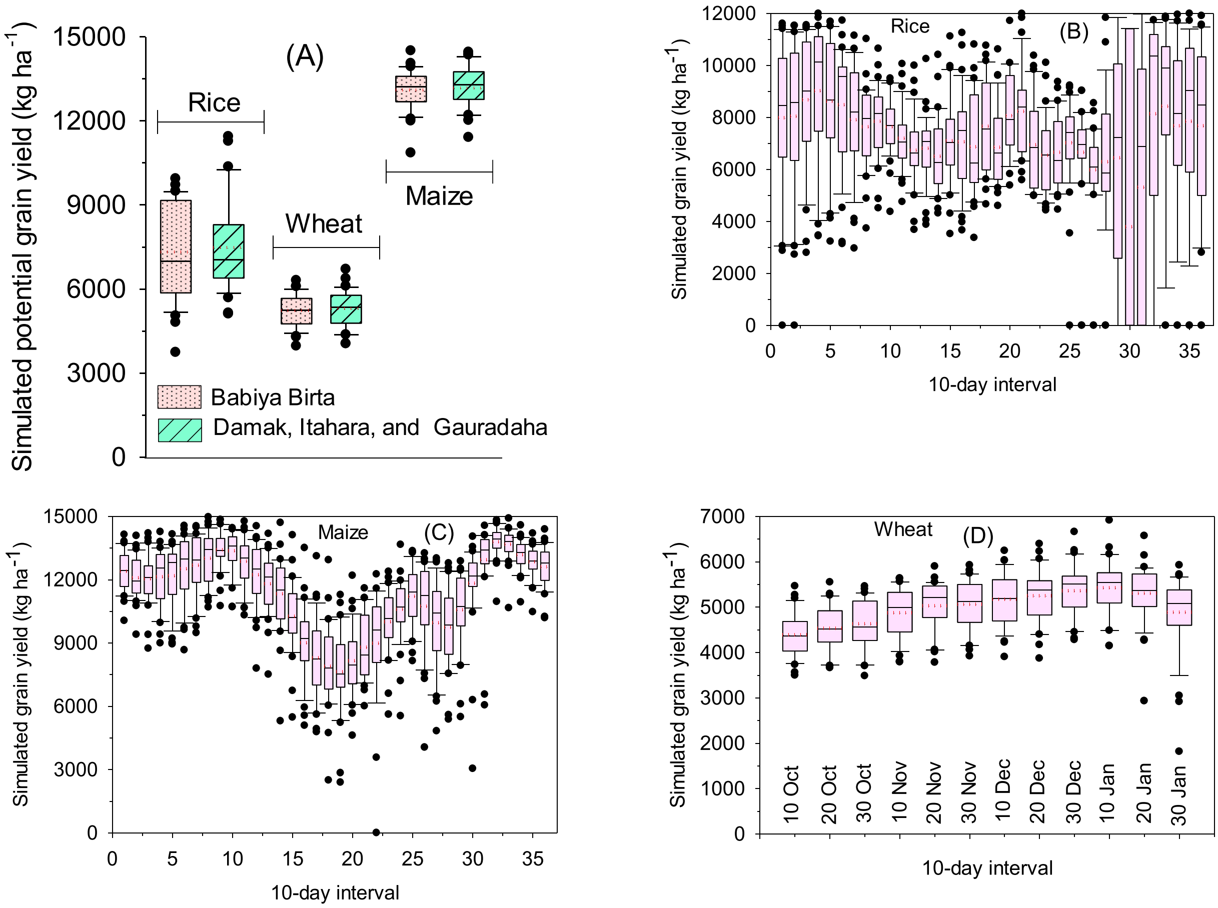

Fig. 6. Model simulated climatic potential yield of rice, wheat and maize in four on-farm trial sites in the EIGP of Nepal using long-term climatic data from 1985 to 2018. Red dotted line inside the box is the mean and the horizontal line the median in four sites. Rice transplanted on 25th June; maize seeded on 10th December and wheat seeded on 10th December (A); long-term simulated potential yield of rice (B) and maize (C) under different seeding dates at 10 days interval starting from January 1st to December 30th, and long-term simulated yield of wheat with seeding starting from 1st of October to 30th of January (D). Simulations in B, C, and D are for Babiya Birta using long-term climatic weather data 1985–2018. Red dotted marks the mean and the black solid line median inside the box.

Table 3
Potential yield and yield gaps (Kg ha^{-1}) for rice, wheat and maize for four villages in the EIGP of Nepal.

Crop	Village	FP	NE	PY	YG1	YG2
		Kg ha^{-1}				
Rice	Babiya birta	3855	5267	7332	3478	2066
	Itahara	3823	5158	7518	3695	2360
	Gauradaha	3708	4952	7518	3811	2567
	Damak	3742	4846	7518	3777	2673
Wheat	Babiya birta	2577	3202	5178	2601	1977
	Itahara	2292	2860	5356	3065	2497
	Gauradaha	2100	3028	5356	3257	2329
	Damak	2581	3149	5356	2775	2207
Maize	Babiya birta	4708	9940	13,175	8468	3235
	Itahara	5649	10,241	13,263	7614	3023
	Gauradaha	6921	10,151	13,263	6342	3113
	Damak	6254	9535	13,263	7009	3729

YG1 = PY-FP; YG2 = PY-NE; FP; Farmer's fertilizer practice; NE = Nutrient Expert; PY=Potential yield; FP and NE yields are averages of all farmers over two years; Potential yields are long-term (1985–2018) mean simulated yields for planting dates of 25 June for rice and 10 December for maize and wheat.

across crops and villages. Data also reveal that the difference between YG1 and YG2 was smallest in wheat and largest in maize (Table 3). Devkota et al., 2016, 2021 reported attainable yield gap variability of more than 3.5 t ha^{-1} for maize in the hill districts and 2–3 t ha^{-1} for rice in the western plain region of Nepal.

Research has shown that 80 to 90% of PY (called attainable yield) can be obtained in the field with best management practices (Timsina et al., 2010, 2018). Our study identifies considerable gaps in all crops between attainable yield and those obtained from the on-farm trials. All trials were managed by farmers and while they were encouraged to follow local best management practices, crop management and input levels among farmers differed considerably. The study highlights opportunities to close the attainable yield gaps in the three cereals through improved site-specific nutrient management.

This study has identified plenty of scopes to close rice yield gap in the EIGP of Nepal through timely transplanting, adoption of better crop establishment method, assured irrigation, and optimization of N application rates (Devkota et al., 2019). Our results also suggest that there is much larger scope for increasing the wheat yields in farmers' fields as well as in improving the yield with NE-based fertilizer recommendation in all sites. In maize, however, there is larger scope for increasing yield in farmers' fields and reducing yield gaps through improved nutrient management. An earlier study in Eastern and Central Terai of Nepal also revealed large gaps between potential and research station yields, between research station and farmer's field yields, and between potential and farmer's field yields, with larger gaps between potential and farmers' fields than the other two yield gap types for several crops (Amgain and Timsina, 2005).

Initial soil analysis showed large variability in soil pH and all analysed nutrients. There was also a large variability in pH and macro- and micro-nutrient contents of farmyard manure (FYM) and poultry manure applied to crops across the four villages (**Supplementary Table 6**). In general, Itahara had the lowest and Babiya Birta had the highest contents of macro- and micro-nutrients. The results of this study indicate variability in soil properties across sites even though they were located close to each other, suggesting a significant variability in indigenous nutrient supply, possibly due to the differences in irrigation water availability and application, soil parent material and FYM and poultry manure application practices, causing variability in yield gaps. Of all, inappropriate nutrient management in GR and FP was the main factor for causing yield gaps in different crops. Devkota et al. (2018) also reported that due to insufficient fertilizer use among farmers, the attainable yield gap in maize attributed to nutrient limitations was 2.6 t ha^{-1} in hills and 1.9 t ha^{-1} in plain (Terai) and that yield could be increased by 144–336% in Nepal Terai. In addition, farmers' socio-economic conditions and prevailing institutional factors also cause yield gaps between potential or attainable yields and farmer's yield (Andualem et al., 2016). This is beyond the scope of this study. Future research should analyse more comprehensibly the biophysical and socio-economic factors responsible for cereal yield gaps in smallholder farmers' fields in the EIGP of South Asia.

3.8. Grain yield prediction using random Forest

The Random Forest (RF) model showed perfect relationship between measured and predicted yield of rice with OOB R^2 of 0.99 for all nutrient management practices (Fig. 7). For NE-based recommendation, the highest influencing factor for predicting rice yield was grain N uptake (100%) followed by grain K and grain P uptakes (both 85–90%). For predicting yield under FP and GR, uptakes of all nutrients appeared influential while both grain P and grain K uptakes exhibited 100% influence (Fig. 7). The RF model also showed perfect relationships for wheat and maize with OOB R^2 of 0.99 for both crops (Supplementary Figs. 6 and 7). The relative importance of the RF predictor variables for maize yield showed that for NE-based recommendation, grain K uptake was of highest importance followed by grain N and grain P uptakes (>90%). Similarly, for FP, grain P uptake was of highest importance followed by grain K and grain N uptakes (**Supplementary Fig. 6**). For predicting wheat yield under NE, grain K uptake (100%) showed the highest influence followed by grain N uptake (95%) and grain P uptake (85%). Under FP, however, both grain P and grain K uptakes exhibited the highest influence (100%) followed by grain N uptake (95%) (**Supplementary Fig. 7**). The RF modelling analysis in this study was thus able to identify the relative importance of factors influencing grain yields of all cereals for all nutrient management practices. Overall, the present study highlights that RF helps to explain if the soil has sufficient amount of plant available N/P/K (through indigenous supply as well as external input), it is highly likely that there will be high plant N/P/K uptake and higher yield. Therefore, higher plant N/P/K uptake is an indication that soil has the ability supply sufficient N/P/K, and plant will absorb and utilize that N/P/K (called internal use efficiency). Based on our results, N was the most influencing nutrient for rice while P and K were influential for wheat and maize. Timsina et al. (2010) explains that in puddle transplanted rice, the reduced environment triggers release of

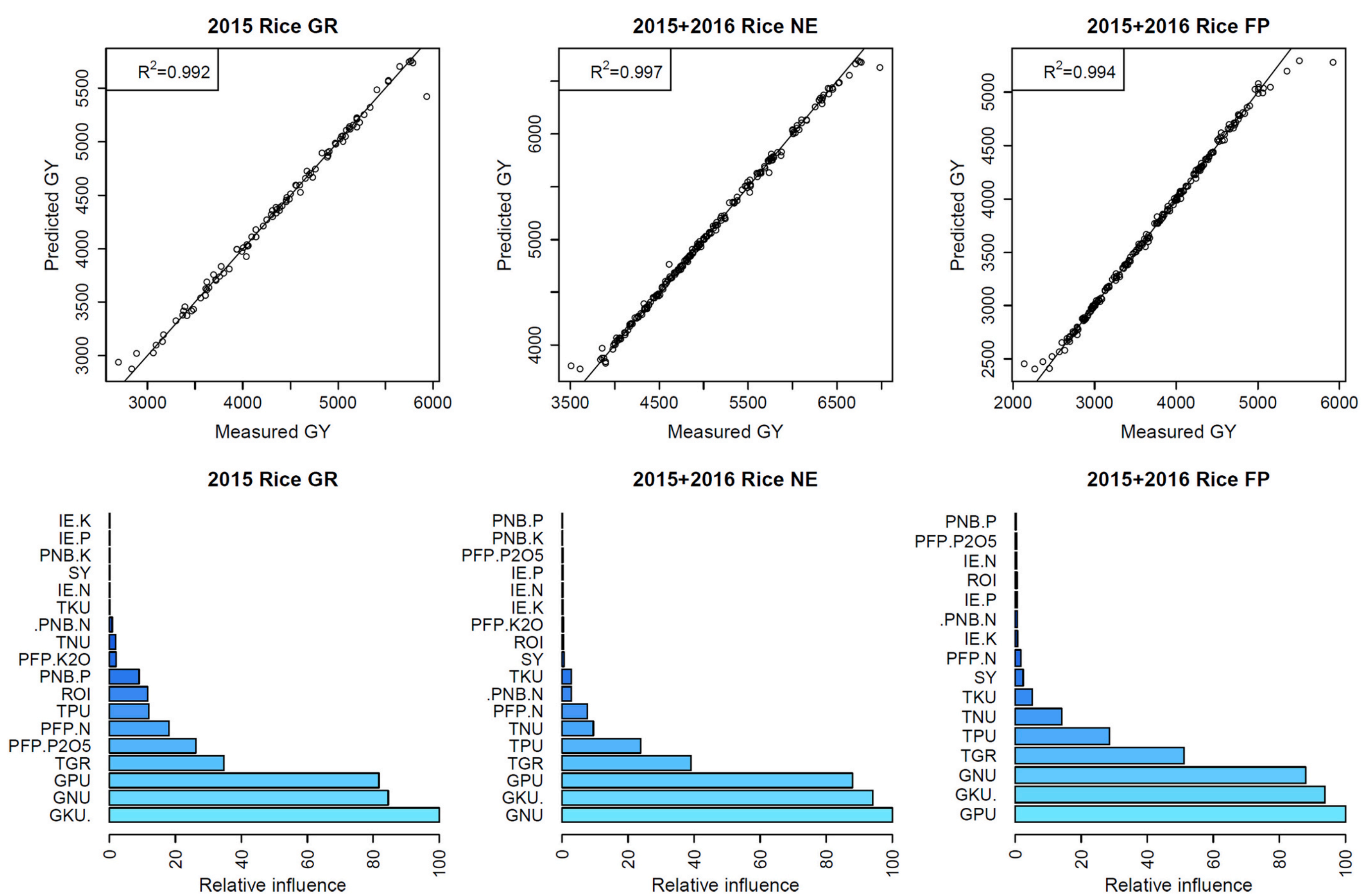

Fig. 7. Plots showing (a: upper row with three quadrants) measured vs. predicted rice grain yield under three nutrient management practices via Random Forest, and (b: lower row with three quadrants) Random Forest variable importance plot for data from four on-farm trial sites in the Eastern IGP of Nepal. Variables used: SY: straw yield; RoI: return on fertilizer investment; PFP N: partial factor productivity of N; GNU: grain N uptake; TNU: total N uptake; IE N: internal efficiency of N; PNB N: partial nitrogen balance; PFP P_2O_5: partial factor productivity of P_2O_5; GPU: grain P uptake; TPU: total P uptake; IE P: internal efficiency of P; PNB P: partial phosphorus balance; PFP K_2O: partial factor productivity of K_2O; GKU: grain K uptake; TKU: total K uptake; IE K: internal efficiency of K; PNB K: partial potassium balance.

P and K from the soil matrix minimizing the likelihood of P and K response in soils with adequate supply of these two nutrients. Such release seizes when the growing environment changes to a more oxidative one in the case of wheat and maize.

Zhan et al. (2016) concluded that K optimization must be considered in management decisions for high-yielding wheat production. Likewise, Gnanasundari et al. (2018) showed a significant response in maize grain yield up to 120 kg K_2O ha^{-1} given that K helps in mitigating biotic and abiotic stresses, ultimately improving the quality of maize. Importantly, ROI also exhibited moderate influence in predicting wheat grain yield under all treatments. A recent yield gap study using RF in Nepal (Devkota et al., 2021) has also highlighted balanced fertilizer application as the major determinant for closing yield gap of rice in the plains of the EIGP. A global study also suggested nutrients and water as main factors for closing the crop yield gaps (Muesller et al., 2012). While we recognise the importance of socio-economic factors determining the input use by smallholders and yield variabilities and the usefulness of partial dependence plots in explaining the yield influencing factors (Dutta et al., 2020; Devkota et al., 2021; Paudel et al., 2021), we didn't include these in the current analysis due to limitations of resources. To better predict and explain the variability of the cereal yields and strengthen the applicability of RF in cereal production systems in the EIGP, we recommend that future research include analysis using the socio-economic factors and the partial dependence plots.

4. Conclusions

The present study highlighted the gaps between the farmer's yield and attainable and potential yields for the three major cereal crops of the EIGP of Nepal; it suggests nutrient recommendation with Nutrient Expert® (NE) DSS tool, along with optimum planting dates, as management strategies to minimize the cereal yield gaps. The risk analysis showed that at a given probability level, NE always resulted in higher yields of all cereals than government recommendation or farmer's practice. The PFP values showed that the participatory farmers in on-farm trials are applying sub-optimal amounts of fertilizers in all cereals, and hence could be causing nutrient mining. The study also demonstrated that the use of NE helps improve economics along with NUE-related performance indicators such as internal efficiency, partial nutrient balance and partial factor productivity over farmers' fertilizer practice and government recommendation. The APSIM model estimated the potential yields of the three major cereals and identified their optimum plating times. The yield variations across four villages in two districts were also observed suggesting a SSNM approach works better over government blanket recommendations as common in much of the EIGP of South Asia.

Using the RF models, the study predicted the expected yields with varied scenarios and found significant correlation between expected and observed yields. The relative importance of the RF predictor variables suggested variations in grain yield of the three cereals across the three nutrient management practices. The RF models showed that grain N uptake of highest relative importance for explaining the variability of grain yield of rice while grain K uptake of highest importance for yields of wheat and maize. Similar studies with larger sample size across varied agro-climatic zones in the EIGP and much of South Asia would help policy makers consider DSS tools and machine learning approaches suitable for upscaling and large-scale adoption by smallholder farmers.

Declaration of Competing Interest

The author declares that the research as well as the article is original in nature and does not have any conflict of interest.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.agsy.2021.103181.

References

Amgain, L.P., Timsina, J., 2005. Crop and cropping systems research at IAAS Rampur Chitwan: A review. J. Inst. Agric. Anim. Sci. 26, 1–22.

Amgain, L.P., Timsina, J., Dutta, S., Majumdar, K., 2021. Nutrient Expert®-Rice: an alternative fertilizer recommendation strategy to improve productivity, profitability and nutrient use efficiency of rice in Nepal. J. Plant Nutr. https://doi.org/10.1080/01904167.2021.1889590.

Andualem, E., Silva, J., Kooistra, L., Reidsma, P., 2016. Review of yield gap explaining factors and opportunities for alternative data collection approaches. Eur. J. Agron. 82 https://doi.org/10.1016/j.eja.2016.06.016.

Banerjee, H., Goswami, R., Chakraborty, S., Dutta, S., Majumdar, K., Satyanarayana, T., Jat, M.L., Zingore, S., 2014. Understanding biophysical and socio-economic determinants of maize (*Zea mays* L.) yield variability in eastern India. NJAS–Wageningen J. Life Sci. 70–71, 79–93.

Bates, D.M., Maechler, M., Bolker, B., Walker, S., 2015. Fitting linear mixed-effects models using lme4. J. Stat. Softw. 67 (1), 1–48.

Boulesteix, A.L., Janitza, S., Kruppa, J., Konig, I.R., 2012. Overview of random Forest methodology and practical guidance with emphasis on computational biology and bioinformatics. Wiley Interdisciplinary Reviews: Data Min. Knowl. Disc. 2, 493–507.

Bouman, B.A.M., Kropff, M.J., Wopereis, M.C.S., ten Berge, H.F.M., van Laar, H.H., 2001. ORYZA2000: Modeling Lowland Rice. IRRI Book. International Rice Research Institute (IRRI), Philippines (No. 281825).

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

Brentrup, F., Pallière, C., 2010. Nitrogen Use Efficiency as an Agro-Environmental Indicator. Proceedings of the OECD Workshop on OECD Agri-environmental Indicators: Lessons Learned and Future Directions, 23–26 March 2010. OECD, Leysin, Switzerland.

Buresh, R., Pampolino, M., Witt, C., 2010. Field-specific potassium and phosphorus balances and fertilizer requirements for irrigated rice-based cropping systems. Plant Soil 335, 35–64.

Chuan, L., He, P., Pampolino, M.F., Johnston, A.M., Jin, J., Xu, X., Zhao, S., Qiu, S., Zhou, W., 2013. Establishing a scientific basis for fertilizer recommendations for wheat in China: yield response and agronomic efficiency. Field Crop Res. 140, 1–8.

Cooper, P.J.M., Dimes, J., Rao, K.P.C., Shapiro, B., Shiferaw, B., Twomlow, S., 2008. Coping better with current climatic variability in the rain-fed farming systems of sub-Saharan Africa: an essential first step in adapting to future climate change? Agric. Ecosyst. Environ. 126, 24–35.

CSISA, 2017. Cereal Systems Initiatives for South Asia (CSISA) Annual Report, Cereal Systems Initiatives for South Asia (CSISA). http://csisa.org/wp-content/uploads/sites/2/2014/06/CSISA-Phase-III-Annual-Report-2016.pdf.

Devkota, K.P., Devkota, M., Poudel, G., McDonald Andrew, 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. Accepted, In press.

Devkota, K.P., McDonald, A.J., Khadka, A., Khadka, L., Paudel, G., Devkota, M., 2015. Decomposing maize yield gaps differentiates entry points for intensification in the rainfed mid-hills of Nepal. F. Crop. Res. 179, 81–94. https://doi.org/10.1016/j.fcr.2015.04.013.

Devkota, K.P., McDonald, A.J., Khadka, L., Khadka, A., Paudel, G., Devkota, M., 2016. Fertilizers, hybrids, and the sustainable intensification of maize systems in the rainfed mid-hills of Nepal. Eur. J. Agron. 80, 154–167. https://doi.org/10.1016/j.eja.2016.08.003.

Devkota, K.P., Devkota, M., Khadka, L., Khadka, A., Poudel, 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. 8, 46–62.

Devkota, M., Devkota, K.P., Acharya, S., McDonald, A.J., 2019. Increasing profitability, yields and yield stability through sustainable crop establishment practices in the rice-wheat systems of Nepal. Agric. Syst. 173, 414–423. https://doi.org/10.1016/j.agsy.2019.03.022.

Dijkshoorn, K., Huting, J., 2009. Soil and Terrain Database for Nepal. Report 2009/01. ISRIC- World Soil Information, Wageningen, 29p. http://www.isric.org.

Dobermann, A., 2007. Nutrient use efficiency – measurement and management. In: "IFA International Workshop on Fertilizer Best Management Practices", Brussels, Belgium, pp. 1–28.

Dobermann, A., Cruz, P.C. Sta, Cassmann, K.G., 1996. Fertilizer inputs, nutrient balance, and soil nutrient-sup-plying power in intensive, irrigated rice systems. I. Potassium uptake and K balance. Nutr. Cycl. Agroecosyst. 46, 1–10.

Dobermann, A., Witt, C., Dawe, D., Abdulrachman, S., Gines, H.C., Nagarajan, R., Satawathananont, S., Son, T.T., Tan, P.S., Wang, G.H., Chien, N.V., Thoa, V.T.K., Phung, C.V., Stalin, P., Muthukrishnan, P., Ravi, V., Babu, M., Chatuporn, S., Sookthongsa, J., Sun, Q., Fu, R., Simbahan, G.C., Adviento, M.A.A., 2002. Site-specific nutrient management for intensive rice cropping systems in Asia. Field Crop Res. 74, 37–66.

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. https://doi.org/10.1016/j.agsy.2020.102826.

Dutta, S.K., Chakraborty, S., Banerjee, H., Goswami, R., Majumdar, K., Li, B., Jat, M.L., 2020. Maize yield in smallholder agriculture system: an approach integrating socio-economic and crop management factors. PLoS One 15 (2), e0229100.

E. U. Nitrogen Expert Panel, 2015. Nitrogen use efficiency (NUE) an indicator for the utilization of nitrogen in food systems. WWW Document. In: Wageningen Univ. Alterra, Wageningen, Netherlands. URL. http://eunep.com/wp-content/uploads/2017/03/N-ExpertPanel-NUE-Session-1.pdf (accessed 9.11.18).

FAO, IFAD, UNICEF, WFP and WHO, 2018. The State of Food Security and Nutrition in the World 2018. Building Climate Resilience for Food Security and Nutrition. Rome, FAO.

FAOSTAT, 2020. United Nations Food and Agricultural Organisation [WWW Document]. URL. http://www.fao.org/faostat/en/#data (accessed 4.14.19).

Fixen, P., Brentrup, F., Bruulsema, T., Garcia, F., Norton, R., Zingore, S., 2015. Chapter 1. Nutrient/Fertilizer Use Efficiency: Measurement, Current Situation and Trends. IFA, IWMI, IPNI and IPI, April 2014. Copyright 2014 IFA, IWMI, IPNI and IPI (All rights reserved).

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A., Michaelsen, J., 2015. The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. Sci. Data 2, 150066.

Gathala, M.K., Timsina, J., Islam, M.S., Krupnik, T.J., Bose, T.R., Islam, N., Rahman, M. M., Hossain, M.I., Harun-Ar-Rashid, M., Ghosh, A.K., Hasan, M.M.K., Khayer, M.A., Islam, M.Z., Tiwari, T.P., McDonald, A., 2016. Productivity, profitability, and energetics: A multi-criteria assessment of farmers' tillage and crop establishment options for maize in intensively cultivated environments of South Asia. Field Crop Res. 186, 32–46.

Gaydon, D.S., Balwinder-Singh Wang, E., Poulton, P.L., Ahmad, B., Ahmed, F., Akhter, S., Alif, I., Amarasingh, R., Chaki, A.K., Chen, C., Choudhury, B.U., Dara, R., Das, A., Hochman, Z., Horan, H., Hosang, E.Y., Vijaya Kumar, P., 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., Shamim, M., Subash, N., Suriadi, A., Suriyagod, L.D.B., Wang, G., Wang, J., Yadav, R.K., Roth, C.H., 2017. Evaluation of the APSIM model in cropping systems of Asia. Field Crop Res. 204, 52–75.

Gnanasundari, R., Sellamuthu, K.M., Malathi, P., 2018. Effect of potassium on growth, yield and NPK uptake of hybrid maize in black calcareous soil. Madras Agric. J. 106 (1–3), 32–37.

Holzworth, D.P., Huth, N.I., de Voil, 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.

Islam, S., Gathala, M.K., Tiwari, T.P., Timsina, J., Laing, A.M., Maharjan, S., Chowdhury, A.K., Bhattacharya, P.M., Dhar, T., Mitra, B., Kumar, S., Srivastwa, P.K., Dutta, K.S., Shrestha, R., Manandhar, S., Shrestha, S.R., Paneru, P., Siddquie, N., Hossain, A., Islam, R., Ghosh, A.K., Rahman, M.A., Kumar, U., Rao, K.K., Gérard, B., 2019. Conservation agriculture for sustainable intensification: an opportunity to increase crop, system yields and water productivity for smallholders of the eastern Gangetic plain. Field Crop Res. 238, 1–17.

Jeong, J.H., Resop, J.P., Mueller, N.D., Fleisher, D.H., Yun, K., Butler, E.E., et al., 2016. Random Forests for global and regional crop yield predictions. PLoS One 11 (6), e0156571. https://doi.org/10.1371/journal.pone.0156571 (IPNI, 2017).

Jones, J.W., Hoogenboom, G., Porter, C.H., Boote, K.J., Batchelor, W.D., Hunt, L.A., Wilkens, P.W., Singh, U., Gijsman, A.J., Ritchie, J.T., 2003. The DSSAT cropping system model. Eur. J. Agron. 18, 235–265. https://doi.org/10.1016/S1161-0301(02)00107-7.

Krupnik, T.J., Ahmed, Z.U., Timsina, J., Shahjahan, M., Kurishi, A.S.M.A., Rahman, S., Miah, A.A., Gathala, M.K., McDonald, A., 2015a. Forgoing the fallow in Bangladesh's stress-prone coastal deltaic environments: effect of sowing date, nitrogen, and genotype on wheat yield in farmers' fields. Field Crop Res. 170, 7–20.

Krupnik, T.J., Ahmed, Z.U., Timsina, J., Yasmin, S., Hossain, F., Mamun, A., et al., 2015b. Untangling crop management and environmental influences on wheat yield variability in Bangladesh: an application of nonparametric approaches. Agric. Syst. 139, 166–179.

Ladha, J., Pathak, S., Krupnik, T., Six, J., Kessel, C., 2005. Efficiency of fertilizer nitrogen in cereal production: Retrospects and prospects. Adv. Agron. 87, 85–156. https://doi.org/10.1016/S0065-2113(05)87003-8.

Liu, X., He, P., JY, Jin, Zhou, W., Sulewski, G., Phillips, S., 2011. Yield gaps, indigenous nutrient supply, and nutrient use efficiency of wheat in China. Agron. J. 103, 1452. https://doi.org/10.2134/agronj2010.0476.

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.

Majumdar, K., Sanyal, S.K., Dutta, S.K., Satyanarayana, T., Singh, V.K., 2016. Nutrient mining: addressing the challenges to soil resources and food security. In: Singh, U., Praharaj, C.S., Singh, S.S., Singh, N.P. (Eds.), Biofortification of Food Crops. Springer, India, pp. 177–198. https://doi.org/10.1007/978-81-322-2716-8_14.

Mandal, M.K., Dutta, S.K., Majumdar, K., 2016. Balanced fertilization through nutrient expert® for profitable rice production. SATSA Mukhapatra - Annual Tech. Issu. 20, 113–119.

Marahatta, S., Acharya, R., Joshi, P.P., 2018. Simulation of growth and yield of rice and wheat varieties under varied agronomic management and changing climatic scenario under subtropical condition of Nepal. J. Agric. For. Univ. 2, 141–156.

Muesller, N.D., Gerber, J.S., Johnston, M., Ray, D.K., Ramankutty, N., Jonathan, A.F., 2012. Closing yield gaps through nutrient and water management. Nature 490, 254–257.

NASA POWER, 2020. Prediction of Worldwide Energy Resource [WWW Document]. URL. https://power.larc.nasa.gov/common/php/POWER_ParametersAgro.php (accessed 2.12.20).

Pampolino, M.F., Manguiat, I.J., Ramanathan, S., Gines, H.C., Tan, P.S., Chi, T., Rajendran, R., Buresh, R.J., 2007. Environmental impact and economic benefits of site-specific nutrient management (SSNM) in irrigated rice systems. Agric. Syst. 93, 1–24.

Pampolino, M.F., Witt, C., Pasuquin, J.M., Johnston, A., Fisher, M.J., 2012a. Development approach and evaluation of the nutrient expert software for nutrient management in cereal crops. Comput. Electron. Agric. 88, 103–110.

Pampolino, M., Majumdar, K., Jat, M.L., Satyanarayana, T., Kumar, A., Shahi, V.B., Gupta, N., Singh, V., 2012b. Development and evaluation of Nutrient Expert for wheat in South Asia. Better Crops with Plant Food 96 (3), 29–31.

Pandey, S., Bhatta, N.P., Paudel, P., et al., 2018. Improving fertilizer recommendations for Nepalese farmers with the help of soil-testing mobile van. J. Crop Improv. 32, 19–32.

Pathak, H., Aggarwal, P.K., Rötter, R.P., Kalra, N., Bandyopadhaya, S., Prasad, S., van Keulen, H., 2003. Modelling the quantitative evaluation of soil nutrient supply, nutrient use efficiency, and fertilizer requirements of wheat in India. Nutr. Cycl. Agroecosyst. 65 (2), 65. https://doi.org/10.1023/A:1022177231332.

Paudel, D., Boogaard, H., de Wit, A., Janssen, S., Osinga, S., Pylianidis, C., Athanasiadis, I., 2021. Machine learning for large-scale crop yield forecasting. Ag Systems 187, 103016. https://doi.org/10.1016/j.agsy.2020.103016.

Pradhan, P., Fischer, G., van Velthuizen, H., Reusser, D.E., Kropp, J.P., 2015. Closing yield gaps: how sustainable can we be? PLoS One 10 (6), e0129487. https://doi.org/10.1371/journal.pone.0129487.

Ray, K., Banerjee, H., Bhattacharya, K., Dutta, S., Phonglosa, A., Pari, A., Sarkar, S., 2017. Site-specific nutrient management for maize hybrids in an inceptisol of West Bengal, India. Experim. Agric. 54, 874–887.

R-core Team, 2020. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL. https://www.R-project.org/.

Roberts, T.L., 2007. Right product, right rate, right time and right place the foundation of best management practices for fertilizer. In: Fertilizer Best Management Practices. General Principles, Strategy for their Adoption, and Voluntary Initiatives vs. Regulations. Proc. of IFA International Workshop, 7–9 March 2007, Brussels, Belgium. International Fertilizer Industry Association, Paris, France, pp. 29–32.

Rurinda, J., Zingore, S., Jibrin, J.M., Balemi, T., Masuki, K., Anderson, J.A., Pampolino, M.F., Mohammed, I., Mutegi, J., Kamara, A.Y., Vanlauwe, B., Craufurd, P.Q., 2020. Science-based decision support for formulating crop fertilizer recommendations in sub-Saharan Africa. Agric. Syst. 180, 102790.

Sapkota, T.B., Majumdar, K., Jat, M.L., Kumar, A., Bishnoi, D.K., McDonald, A.J., et al., 2014. Precision nutrient management in conservation agriculture-based wheat production of Northwest India: profitability, nutrient use efficiency and environmental footprint. Field Crop Res. 155, 233–244.

Sapkota, T., Jat, M., Rana, D., Khatri-Chhetri, A., Jat, H.S., Bijarniya, D., Sutaliya, J., Kumar, M., Singh, L.K., Jat, R., Kalvaniya, K., Prasad, G., Sidhu, H., Rai, M., Satyanarayana, T., Majumdar, K., 2021. Crop nutrient management using Nutrient Expert improves yield, increases farmers' income and reduces greenhouse gas emissions. Sci. Rep. 11 https://doi.org/10.1038/s41598-020-79883-x.

Setiyono, T.D., Walters, D.T., Cassman, K.G., Witt, C., Dobermann, A., 2010. Estimating the nutrient uptake requirements of maize. Field Crop Res. 118, 158–168.

Siddique, K., Li, X., 2019. The potentials of future smart food for mountain agriculture achieving zero hunger: nutrition, climate-resilient, economic and social benefits. In: Mountain Agriculture: Opportunities for Harnessing Zero Hunger in Asia. Food and Agriculture Organization of the United Nations, FAO, pp. 45–55.

Snedecor, G.W., Cochran, W.G., 1989. Statistical Methods, Eighth edition. Iowa State University Press, USA.

Snyder, C.S., Bruulsema, T.W., 2007. Nutrient Use Efficiency and Effectiveness in North America. Indices of Agronomic and Environmental Benefits. IPNI publication Ref. # 07076, International Plant Nutrient Institute, Norcross.

Sudhir-Yadav Li, T., Humphreys, E., Gill, G., Kukal, S.S., 2011. Evaluation and application of ORYZA2000 for irrigation scheduling of puddled transplanted rice in North West India. Field Crop Res. 122, 104–117.

Timsina, J., Connor, D.J., 2001. Productivity and management of rice-wheat cropping systems: issues and challenges. Field Crop Res. 69, 93–132.
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., Jat, M.L., Majumdar, K., 2010. Rice-maize systems of South Asia: current status, future prospects and research priorities for nutrient management. Plant Soil 335, 65–82.
Timsina, J., Wolf, J., Guilpart, N., van Bussel, L., Grassini, P., van Wart, J., Hossain, A., Rashid, H., Islam, S., van Ittersum, M., 2018. Can Bangladesh produce enough cereals to meet future demand? Agric. Syst. 163, 36–44.
Tripathi, M.P., Shrestha, J., Gurung, D.B., 2016. Performance evaluation of commercial maize hybrids across diverse Terai environments during the winter season in Nepal. J. Maize Res. Dev. 2, 1–12. https://doi.org/10.3126/jmrd.v2i1.16210.
Van Duivenbooden, N., Witt, C.T., Van Keulen, H., 1996. Nitrogen, phosphorus and potassium relations in five major cereals reviewed in respect to fertilizer recommendations using simulation modeling. Fert. Res. 44, 37–49.
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. Field Crop Res. 143, 4–17.
Wang, J., Vanga, S.K., Saxena, R., Orsat, V., Raghavan, V., 2018. Effect of climate change on the yield of cereal crops: A review. Climate 6, 41.
WFP, 2019. https://www.wfp.org/publications/2019-hunger-map.
Williams, P.C., 1987. Variables affecting near-infrared reflectance spectroscopic analysis. In: Williams, P., Norris, K. (Eds.), Near-Infrared Technology in the Agricultural and Food Industries. Am. Assoc. of Cereal Chemists, St. Paul, MN, pp. 143–167.
Witt, C., Dobermann, A., Abdulrachman, S., Gines, H.C., Wang, G., Nagarajan, R., Satawatananont, S., Son, T.T., Tan, P.S., Tiem, L.V., Simbahan, G.C., Olk, D.C., 1999. Internal nutrient efficiencies of irrigated lowland rice in tropical and subtropical Asia. Field Crop Res. 63, 113–138.
Xu, X., He, P., Qiu, S., Pampolino, M.F., Zhao, S., Johnston, A.M., Zhou, W., 2014. Estimating a new approach of fertilizer recommendation across small-holder farms in China. Field Crop Res. 163, 10–17.
Xu, X., He, P., Zhao, S., Qiu, S., Johnston, A.M., Zhou, W., 2016. Quantification of yield gap and nutrient use efficiency of irrigated rice in China. Field Crop Res. 186, 58–65.
Zhan, A., Zou, C., Ye, Y., Liu, Z., Cui, Z., Chen, X., 2016. Estimating on-farm wheat yield response to potassium and potassium uptake requirement in China. Field Crop Res. 191, 13–19.
Zhang, J., He, P., Xu, X., Wang, Y., Jia, L., Cui, R., Wang, H., Zhao, S., Ullah, S., 2017. Nutrient expert improves nitrogen efficiency and environmental benefits for summer maize in China. Agron. J. 109 https://doi.org/10.2134/agronj2016.08.0477.