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Assessment of nutrient management in major cereals: Yield prediction, energy-use efficiency and greenhouse gas emission

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A R T I C L E I N F O

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A B S T R A C T

Through improved nutrient management, sustainability of cereal production can be achieved by improving crop yield and economic indicators with reduced environmental footprints and energy use. The objectives of this study were to compare the crop yield and economics, and energy and environment related indicators as the measures of sustainability across three nutrient management practices in three major cereals of South Asia. Nutrient Expert (NE) based fertilizer recommendation, government recommendation (GR), and farmers' nutrient management practice (FP) were evaluated in 600 on-farm trials in two eastern Terai districts of Nepal during 2014–2016. The machine learning (Random Forest) approach was used to identify major indicators to predict grain yield variability. The NE-based recommendation had the highest and FP had the lowest grain yield and gross return in all cereals. Farmer's practice had the highest probability of increasing energy-use efficiency (EUE) followed by NE in all cereals. NE had the lowest yield-scaled greenhouse gas emission (greenhouse gas emission intensity; GHGI) in rice and intermediate in maize and wheat compared with GR or FP. Farmers' practice had consistently the highest GHGI in rice and maize while GR had the highest GHGI in wheat. Except for rice in FP, specific energy (SE) followed by EUE were the major predictors of grain yield of all crops in all nutrient management practices. These findings suggest an opportunity for increasing productivity and profitability with lowered GHGI of the major cereals with NE-based fertilizer recommendation and potential for its out-scaling in Nepal and the Eastern Indo-Gangetic Plains of South Asia.

1. Introduction

In recent decades, intensification of agricultural production has been achieved by increasing input application, especially fertilizer, to strengthen the agri-food system and feed the increasing global population (Galloway et al., 2008; Pimentel, 2009). Achieving high crop yield from the conventional production system requires multiple tillage operations for land preparation and planting as well as applications of high amounts of fertilizers, irrigation, and pesticides. These can result in increased energy inputs and consequently increased greenhouse gases (GHG) emissions (Devkota et al., 2020; Gathala et al., 2020). In intensive cereal production systems, energy use is highest from fertilizers followed by fuel use for irrigation and machinery required for tillage and other farm operations (Pimentel, 2009; Gathala et al., 2020). Increased fertilizer application is necessary to increase cereal yields to feed the increasing global population but increased fertilizer use can also emit

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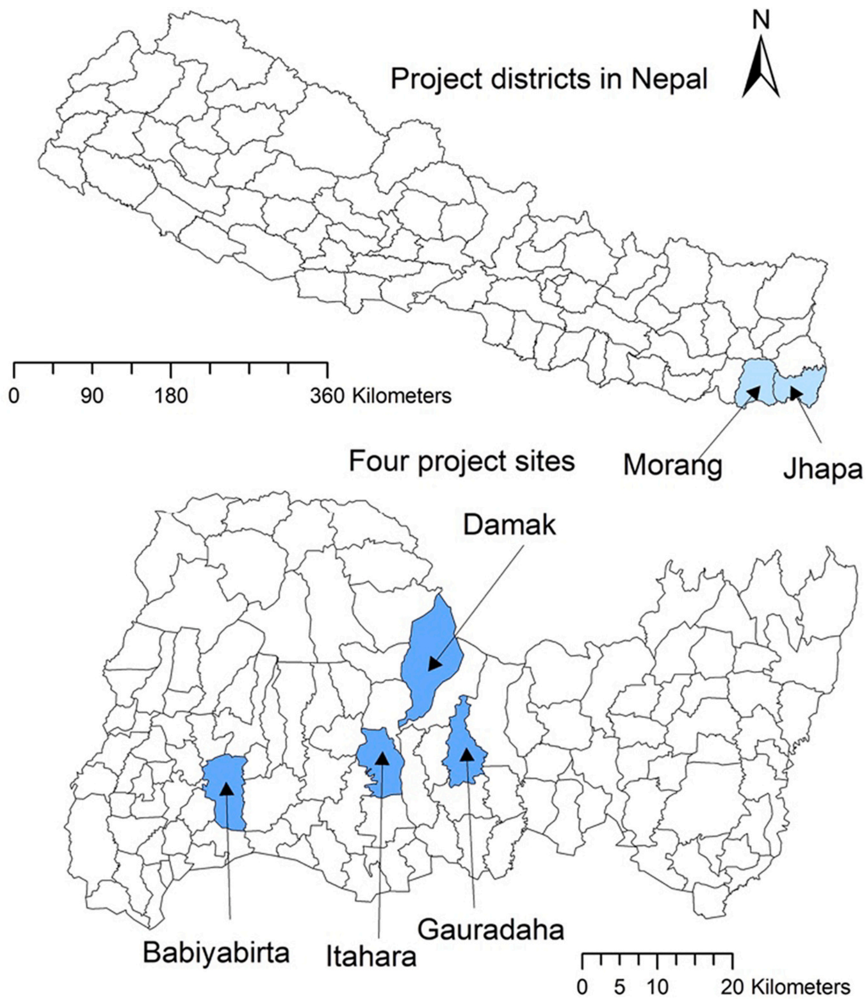

Fig. 1. Map of Nepal showing two on-farm experimentation districts and four project villages in the EIGP of Nepal.

substantial amounts of GHGs and contribute to global warming (Tilman et al., 2001; Snyder et al., 2009; Woods et al., 2010). To develop optimum fertilizer recommendations to crops and simultaneously reduce global warming, fertilizer rates are often determined for site-, soil- and crop-specific situations (Pampolino et al., 2007; Zhu et al., 2019). However, there is an alternative and more robust approach to fertilizer recommendation, known as 'yield-scaled emissions (YSE)' or 'greenhouse gas emission intensity (GHGI)'. This approach considers the trade-off among yield, economics, energy, and GHGs emissions, and has now been used by several researchers for achieving the sustainable intensification of agriculture (Mosier et al., 2006; van Groenigen et al., 2010; Adviento-Borbe et al., 2013).

Optimization of fertilizer use in cereal production can eliminate the chance of over-application and minimizes nutrient mining whereas application of high fertilizer N rates (above-optimal) can result in higher yield-scaled global warming potential (GWP) (Adviento-Borbe et al., 2013; Sainju et al., 2014a, 2014b; Sainju, 2016). Devkota et al. (2019) demonstrated that high rice yields can be achieved with minimal yield-scaled GWP. Yield-scaled GWP in rice can be decreased significantly (by 21%) with optimal N rates compared to no N addition (Pittelkow et al., 2014), but not necessarily in wheat or maize (Sainju, 2016). In these crops, increasing N rates to a certain level decreased GWP and GHGI but when N rates further increased, both these parameters also increased (Sainju et al., 2014a, 2014b). It suggests that excessive N fertilizer application can increase net GHGs emissions. The YSE or GHGI contrasts with promoting conventional practices that do not consider the balance between yield and GHGs emissions (Hillier et al., 2012; Grassini and Cassman, 2012; Linquist et al., 2012a, 2012b). The improved resource-use efficiencies, particularly N-use efficiency (NUE) through improved fertilizer N management have the potential to reduce the total GWP and strengthen the economic and environmental sustainability of the cereal production systems (Pittelkow et al., 2014; Adviento-Borbe et al., 2013; Sainju et al., 2014a, 2014b; Sainju, 2016).

In Nepal, although the overall use of fertilizers in agriculture has increased, farmers' application rates are far lower than the government recommended or crop demand (Devkota et al., 2021; Krupnik et al., 2021; Timsina et al., 2021). Due to large variability in soil types and nutrients within and between fields, the cereal yields and fertilizer-use efficiencies are also low. Thus, alternative nutrient management practices are needed that require the same or lower amounts of fertilizers but still provide high yields with reduced energy use and reduced GHGI. One such management practice is site-specific nutrient management (SSNM), which has the potential to optimize fertilizer use, and increase yield and profitability by reducing GHGI (Dobermann et al., 2004; Dobermann and Cassman, 2005; Dobermann, 2007; Devkota et al., 2018). However, there are no systematic assessments of fertilizer recommendations considering site or soil conditions and crop demand and aiming for increased productivity, profitability, and EUE in the Eastern Indo-Gangetic Plains (EIGP) of South Asia and, in particular, in Nepal. Studies have shown that the decision support system (DSS) tool Nutrient Expert (NE), based on 4R stewardship and SSNM principles (right fertilizer product, right rate, right time, and right place), can optimize nutrient management to increase farmers' income, achieve higher nutrient-use efficiency, and reduce environmental pollution from cereal

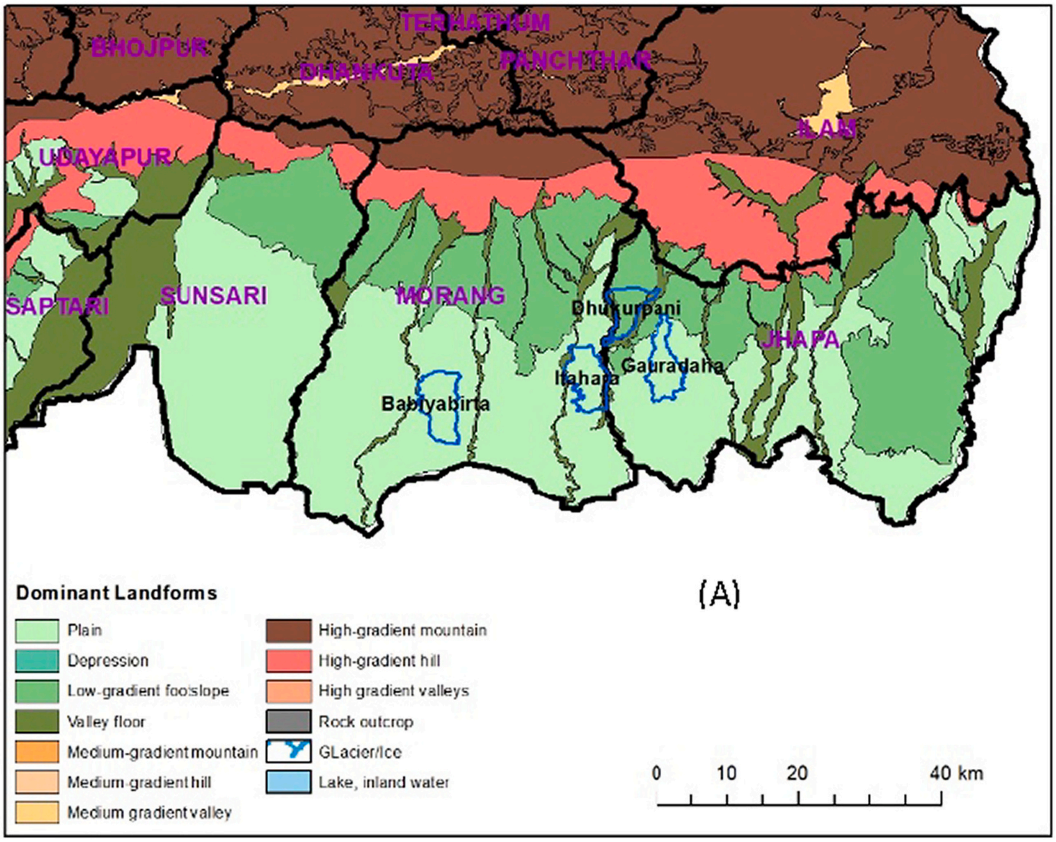

Fig. 2. Dominant landforms in field trials locations (A); dominant parent materials (B), and dominant soils (C) in Jhapa and Morang in the EIGP of Nepal.

production (Amgain et al., 2021; Dutta et al., 2020; Majumdar et al., 2016; Pampolino et al., 2012; Rurinda et al., 2020; Krupnik et al., 2021; Timsina et al., 2021). In addition, machine learning analytics such as Random Forest (RF) could be useful to identify the major predictors and determine the relative importance of those predictors for grain yield (Breiman, 2001; Banerjee et al., 2014; Krupnik et al., 2015; Dutta et al., 2020; Timsina et al., 2021).

However, apart from the handful of peer-reviewed studies, there are no evidence comparing energy use, EUE, EP, and GHGI under various nutrient management practices for the major cereal (rice, wheat, and maize) production systems in Nepal. Further, limited information exists about the synergies or trade-offs among yield, economic, energy, and environmental indicators as affected by nutrient management practices. Improved understanding of energy use and GHGs emissions-related indicators could facilitate the identification of energy-efficient nutrient management options with reduced GHGI without reducing crop yield. In response to the above gaps, we hypothesized that (i) fertilizer rates in cereal crops could be decreased without decreasing crop yields but by reducing yield-scaled GWP, and (ii) fertilizer DSS tools and machine learning approach could help to understand crop yield variability, optimize fertilizer rates, increase nutrient-use efficiency, and reduce GHGI. Thus, the objective of the study was to compare the performance indicators and identify synergies and trade-offs among them across three nutrient management practices for achieving the economic and environmental sustainability of cereal production systems in Nepal and in the EIGP.

2. Materials and methods

2.1. Climate and soil of the experimental site

The on-farm experiments were conducted in two districts - Jhapa (87.70° E 26.61° N) and Morang (87.53° E 26.53° N) - in eastern Nepal (Fig. 1). Two villages from each district (Itahara and Babiya Birta in Morang and Gauradaha and Damak in Jhapa) were selected. Climatic conditions during the experimental period for each village are presented in detail by Timsina et al. (2021). There were similar daily rainfall and maximum and minimum temperature patterns across the four villages. However, soil chemical characteristics differed across fields in each village. Itahara, Babiya Birta, and Gauradaha have plain lands with Eutric gleysols soil while Damak has plain lands with low gradient slope and calcaric and haplic phaezems soil (Fig. 2). The soil types in all four villages have fluvial, non-calcareous parent materials. Initial soil analysis showed that soils across farmers' fields in all villages were acidic with pH ranging from 5.3 to 6.4. Soils of Jhapa were more acidic than those of Morang. Soil organic carbon (SOC) ranged from 0.5 to 0.8, with lower SOC in Jhapa compared to Morang. Soil available P ranged from 14.1 kg ha^{-1} (in Babiya Birta) to 45.1 kg ha^{-1} (in Gauradaha). Soil exchangeable K ranged from 71 to 385 kg ha^{-1}. Soils of Jhapa had the lowest exchangeable K while those of Itahara had medium and Babiyabirta had the highest. Damak had the lowest contents of micronutrients. While there were differences in soil chemical properties among the villages and between districts, there were similarities in weather except in Babiya Birta. Crop, water, weed, and pest and disease management practices varied among villages (see Timsina et al., 2021 for details).

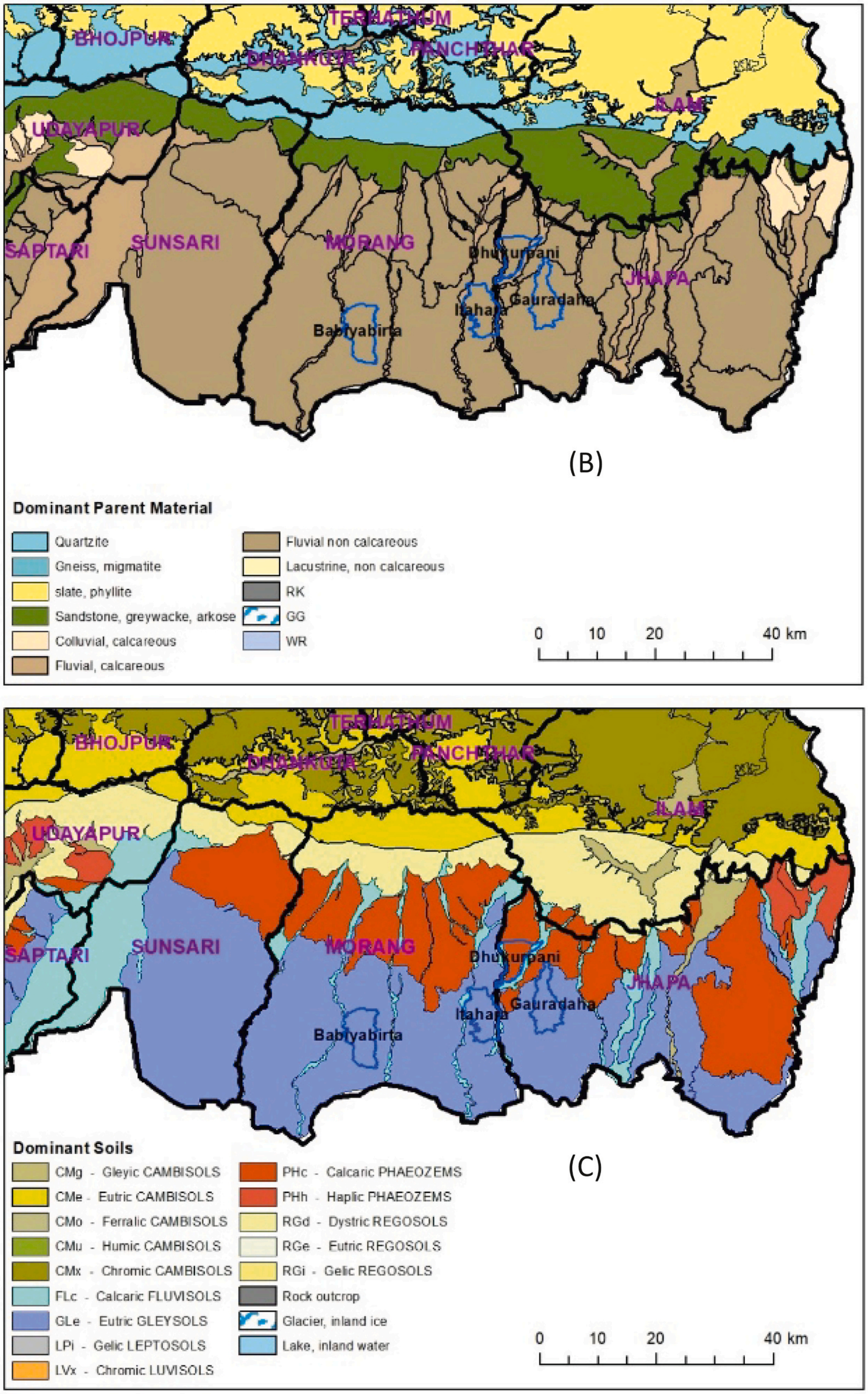

Fig. 2. (*continued*).

2.2. On-farm trials

A total of six hundred on-farm trials in rice, wheat, and maize were conducted over two years from 2014 to 2016 in four villages (each with 50 farming households). Timsina et al. (2021) have described the on-farm trials in detail. Briefly stated, trials in each crop were conducted in 200 farmers' fields. Each farmer (farm) was considered as a replication and three nutrient management treatments were evaluated in each farm. The individual plot size was 100 m^2 for rice and wheat and 150 m^2 for maize, and treatments in each trial were randomly allocated following the principle of randomized complete block design.

The following three treatments were compared in each crop:

T1: farmers' fertilizer practice (based on fertilizer application by farmers in their adjacent plots and was obtained with farmers' interview; fertilizer rates, timing and other management practices varied from farmer to farmer).

T2: fertilizer rates based on NE recommendation (based on farmers' responses to the questionnaire prepared for NE; rates, timing and sources of fertilizers differed across farmers' fields).

T3: fertilizer rates 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; rates and timing were same for all trials and sites).

Before and during the trial implementations, all participant farmers were provided training by researchers on good agricultural practices and on the use of NE software for fertilizer recommendation. Hence, they saw the potential benefits of NE-based recommendations compared to GR from the beginning of the trials. Results from the first-year trials also showed higher yield and profits from NE-based recommendations compared to GR. Hence, farmers preferred to compare only NE-based recommendations together with their practice from the second year onwards. Thus, the NE and FP treatments were implemented by all farmers in both years, while the GR treatment was implemented only in the first year.

The selection of farmers and fields in each village was the joint decision of international and local researchers, extension workers, and the participating farmers. In the NE and GR plots, farmers managed the crops and fields following the fertilizers recommendations as provided by the supervising researcher, while in the FP plots, all inputs and crop management practices were as per farmers' practices. From all 600 farmers, all data required to compute crop productivity, profitability, energy use, and GHGs emissions were recorded.

The Nutrient Expert® model used for NE-based fertilizer recommendation in these trials is described in detail by Timsina et al. (2021). The principles, development, calibration and validation of NE-Rice, NE-Wheat and NE-Maize in different countries are described in several other studies (Amgain et al., 2021; Dutta et al., 2020; Majumdar et al., 2016; Pampolino et al., 2012; Rurinda et al., 2020).

2.3. Machine learning analytics

The Random Forest (RF) model of machine learning has been used in predicting crop yields and understanding yield variability (Jeong et al., 2016; Paudel et al., 2020; Devkota et al., 2021; Timsina et al., 2021). Random Forest is a recursive partitioning-based decision tree and an ensemble learning technique, which combines numerous prediction trees where each tree is built from a bootstrap sample drawn from the training dataset (Breiman, 2001). 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 the trees in the forest. Random Forest uses bootstrap and feature sampling, i.e., row and column sampling. Therefore, RF is not affected by multicollinearity since it picks a different set of features for different models and every model uses a different set of data points (Breiman, 2001). Thus, RF is a suitable algorithm for situations where correlation exists between variables. 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). The missing values in the dataset were imputed by using the k-nearest neighbour (kNN) method. For executing the RF model, instead of splitting the data into calibration and validation sets, the Out-of-Bag (OOB) prediction method, which is very similar to cross-validation, was employed. A total of nine models [3 crops × 3 treatments] were created using the RF algorithm. For the NE and FP treatments, data from both years were combined while for GR, only the first year of data was used. Variables used to predict grain yield in the RF model were total CO_2-eq. emission from N fertilizer, total CO_2-eq. emission from all sources, energy input from fertilizers, total energy use, EUE, and SE.

Table 1
Energy conversion and CO_2-equivalent emission conversion units used to calculate energy inputs and outputs and GHGI under three nutrient management options.

Particulars	Unit	Energy equivalent (MJ $unit^{-1}$)
A. Energy conversion units		
1. Inputs		
a. Human labor	Person-hr	1.96
b. Diesel fuel	litre	56.3
c. Chemical fertilizer		
Elemental nitrogen	kg	66.1
Elemental phosphorus	kg	12.4
Elemental potassium	kg	11.2
d. Seed	kg	15.2
e. Irrigation	mm ha^{-1}	1431
2. Outputs		
a. Grain yield	kg	14.7
b. Straw yield	kg	18.0
B. CO_2-equivalent emission conversion units		
Sources of energy	CO_2 emission (g CO_2-eq. MJ^{-1})	
a. Diesel	MJ	75.2
b. Petrol	MJ	72.3
c. Chemical fertilizer		
N	MJ	50.0
P	MJ	60.0
K	MJ	60.0
S	MJ	60.0
Zn	MJ	60.0
Boron	MJ	60.0
d. Pesticides	MJ	60.0

Source: Adapted and modified from Gathala et al. (2020).

2.4. Energy analysis

In all crops, input applications (e.g., fertilizers, seeds, irrigation water, pesticides, fuel, human labour) used in different treatments and crop outputs (i.e., grain and straw) were recorded from the participating farmers. Inputs and outputs were transformed to energy unit equivalents using the published conversion coefficients to facilitate comparison between treatments (Table 1). The labor used for all farm operations was recorded in each field trial and average values for each treatment in each village were aggregated to the district level. Energy outputs were calculated for both grain and straw yield. Energy analysis and return on investment were computed as follows based on the procedure described by Gathala et al. (2016, 2020):

Total energy use (TEU: MJ ha^{-1}): It is total energy required to produce a crop.

$$TEU = \left[E_m + E_f + E_i\right] \tag{1}$$

where, E_m is the manual energy from labor; E_f is the energy from fuel; and E_i is the energy from all crop production inputs.

Fertilizer energy use (FEU; MJ ha^{-1}): It is fertilizer energy required to produce a crop.

$$FEU = \left[E_n + E_p + E_k\right] \tag{2}$$

where, E_n, E_p and E_k are energy used through N, P, and K fertilizers.

Energy output (EO; MJ ha^{-1}): It is energy produced in grain and straw products.

$$EO = [(GY \text{ x Energy factor}) + (SY \text{ x Energy factor})] \tag{3}$$

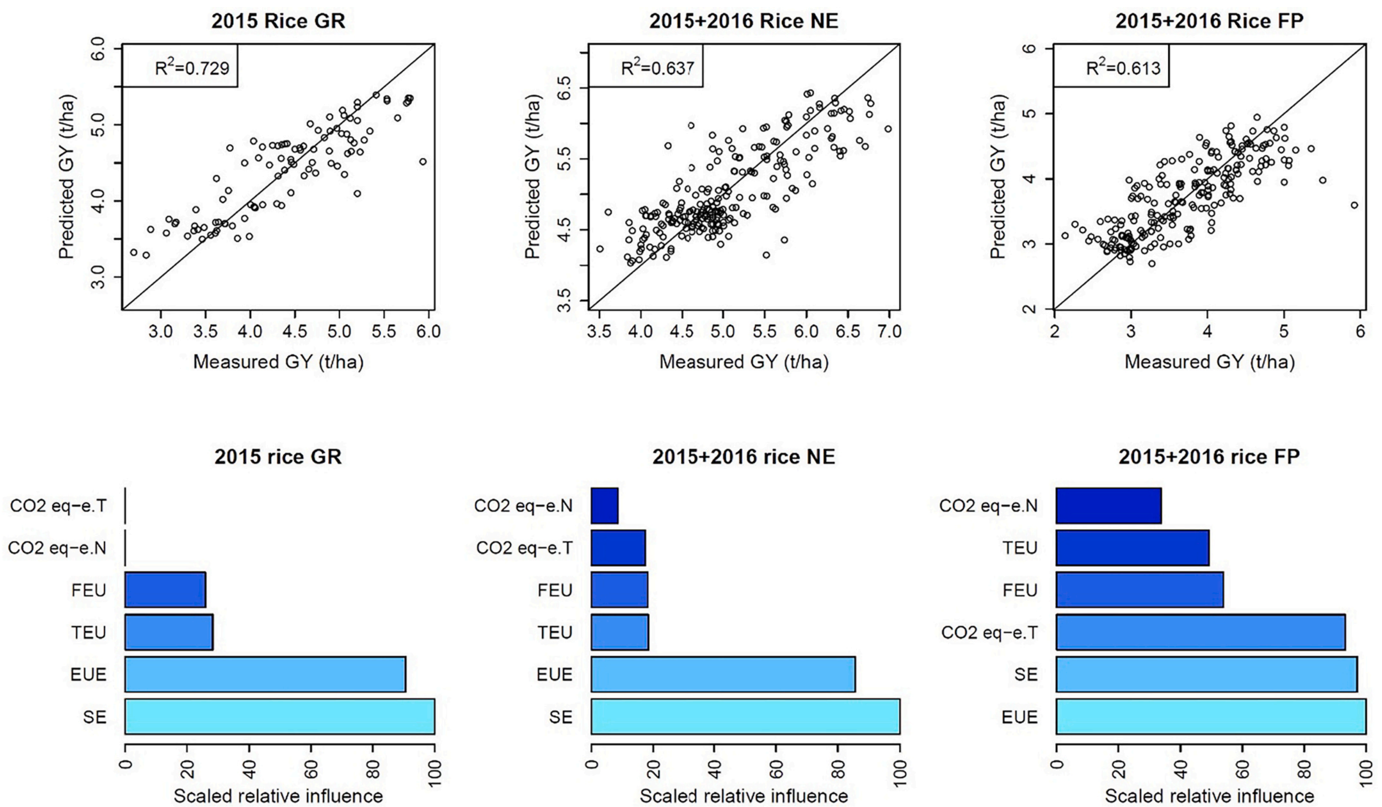

Fig. 3. Measured vs. predicted rice grain yield under Government recommendation (GR), Nutrient Expert recommendation (NE), and Farmers' practice (FP) using random forest model (*Upper row with three quadrants*), and variables explaining yield variability (*Lower row with three quadrants*) in the EIGP of Nepal. GY = grain yield, SE = specific energy, EUE = energy-use efficiency, TEU = total energy use, FEU = fertilizer energy use, CO_2 eq-e.N = CO_2 equivalent emissions from fertilizers, CO_2 eq-e.T = CO_2 equivalent emissions from all sources.

where, GY and SY are grain and straw yields; Energy factor is the specific conversion factor for grain or straw (Table 1).

Energy-use efficiency (EUE): It is the ratio of energy output divided by total energy use through fertilizer (FEU).

$$EUE = \frac{EO}{FEU} \tag{4}$$

Energy productivity (EP, (kg grain MJ^{-1}): It is grain yield divided by energy use through fertilizer.

$$EP = \frac{GY}{FEU} \tag{5}$$

Specific energy (SE, MJ kg^{-1}): It is total energy use divided by total above-ground grain and straw yield.

$$SE = \frac{TEU}{GY + SY} \tag{6}$$

Return on investment (ROI, MJ kg^{-1}): It is gross return divided by total cost of production (TFC).

$$ROI = \frac{\text{Gross return}}{TFC} \tag{7}$$

2.5. Estimation of CO_2-equivalent emissions and GHG emission intensity

CO_2-eq. emissions (kg ha^{-1}) from fertilizers: The total CO_2-eq. emissions from all fertilizers from each treatment in all crops and years were computed as:

$$CO_2\ \text{eq.emissions from fertilizers} = [(\text{Energy eq.from N} + \text{P} + \text{K fertilizers})] \tag{8}$$

Total CO_2-eq emissions from all sources (kg ha^{-1}): These were estimated as emissions generated from the management undertaken to produce a crop such as from fertilizer, fuel, and various farm operations and were calculated for each nutrient management option as follows:

$$\begin{aligned} CO_2\ \text{eq.emissions from all sources} = {} & [(\text{TEU fuel x } CO_2\ \text{eq.}) \\ & + (\text{TEU fertilizers x } CO_2\ \text{eq.}) \\ & + (\text{TEU agrochemicals x } CO_2\ \text{eq.}] \end{aligned} \tag{9}$$

where the TEU terms are the total energy used in each category multiplied by the relevant CO_2-eq. conversion factors as shown in Table 1.

The CO_2-eq. emissions through methane and nitrous oxide (expressed as kg ha^{-1}) were calculated from the conversion factors taken from the literature. In rice, methane emission as affected by water management was computed using the procedure developed by IPCC (2019). In all crops, total N_2O emissions included direct and indirect N_2O emissions which were related to the N fertilizer rate. The calculation methods of direct N_2O emissions (Cui et al., 2013) and indirect N_2O emissions including ammonia (NH_3) volatilization and nitrate (NO_3) leaching (Wu et al., 2014) were calculated as follows:

$$\text{Direct } N_2O \text{ emissions} : 0.576 \text{ x } e^{(0.0049 \times \text{N rate})} \tag{10}$$

Indirect N_2O emissions (sum of NH_3 volatilization and N leaching):

$$NH_3 \text{ volatilization} : 0.24 \times \text{N rate} + 1.30 \tag{11}$$

$$\text{N leaching} : 4.46 \text{ x } e^{(0.0094 \times \text{N rate})} \tag{12}$$

Indirect N_2O emissions were estimated as 1% and 0.75% of NH_3 volatilization and N leaching respectively.

Since the GWP of N_2O and CH_4 is 310 and 25 respectively, their CO_2

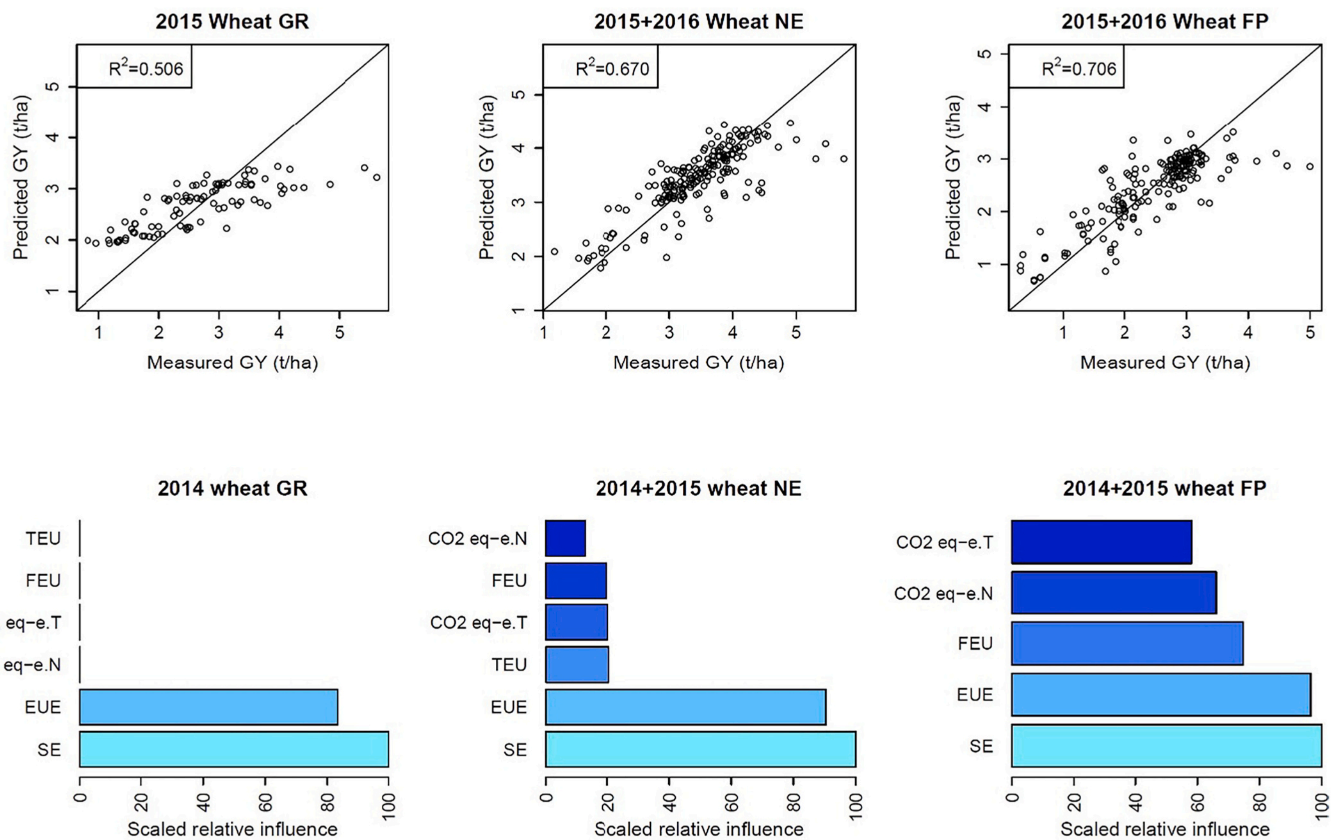

Fig. 4. Measured vs. predicted wheat grain yield under Government recommendation (GR), Nutrient Expert recommendation (NE), and Farmers' practice (FP) using random forest model (*Upper row with three quadrants*), and variables explaining yield variability (*Lower row with three quadrants*) in the EIGP of Nepal. Fig. 3 for the detailed explanation of figure labels.

eq. emissions were calculated as:

$$CO_2 \text{ eq.emissions from } N_2O : N_2O \text{ emissions} \times 310 \quad (13)$$

$$CO_2 \text{ eq.emissions from } CH_4 : CH_4 \text{ emissions} \times 25 \quad (14)$$

***GHG emission intensity* (GHGI; *kg CO_2eq. emission t^{-1}grain yield*):** GHGI provides a useful measure of agronomic performance by integrating production with mitigation goals (Pittelkow et al., 2014; Sainju, 2016) and was calculated as follows:

$$GHGI = \frac{CO_2 \text{ eq.emissions}}{GY} \quad (15)$$

2.6. Risk analysis and multi-criteria assessment

For the risk analysis, descending cumulative distribution functions (CDFs) of EUE, EP and GHGI for various nutrient management options were constructed using data points for two years for NE and FP and one year for GR. Descending CDFs describe the EUE, EP and GHGI for each crop and nutrient management practice. Risk analysis using the CDFs has been found useful in yield, profit, energy, and GHG emissions studies with various cropping systems in the EIGP (e.g., Islam et al., 2019; Gathala et al., 2020). For the multi-criteria assessment of nutrient management options, 'spider' web diagrams (Snapp et al., 2010) were constructed for all crops using multiple economic, energy, and environmental parameters.

2.7. Statistical analysis

The analysis of variance (ANOVA) of various data sets was conducted using the unbalanced general linear model in 'agricolae' package in R version 4.04. As the year x treatment interaction was non-significant, data were combined over years. The ANOVA was conducted for the randomized complete block design (RCBD) with the farmer as replication, and mean separation was performed using the Fisher's Protected Least Significant Difference (LSD) test. Treatment differences were considered statistically significant at $p < 0.05$. Since the normality assumption of the ANOVA was met for all measured parameters, there was no need for data transformation. Correlation and descriptive statistics for different parameters were computed as needed. Trade-offs among yield, profits, energy and environmental parameters were visualized using spider/radar graph (after standardizing the data on 0–1 scale) and box plots were used to show the variability.

3. Results and discussion

3.1. Grain yield prediction using RF algorithm

Across years, the measured grain yield of rice ranged from 2.7 to 5.9 t ha^{-1} in GR, from 3.5 to 7.0 t ha^{-1} in NE, and from 2.1 to 5.9 t ha^{-1} in FP (Fig. 3). The OOB R^2 derived from predictors for GR, NE, and FP were 0.72, 0.63, and 0.61, respectively, indicating that the RF model can predict the yield variability satisfactorily. The model for explaining the rice yield variability showed SE of highest importance followed by EUE and TEU under GR and NE nutrient management practices, while EUE followed by SE and CO2 eq. emissions were the major predictors under FP. In wheat, measured grain yield ranged from 0.8 to 5.6 t ha^{-1} in GR, from 1.2 to 5.7 t ha^{-1} in NE, and from 0.3 to 5.0 t ha^{-1} in FP, with R^2 of 0.50, 0.67, and 0.70, respectively (Fig. 4). Similarly, for wheat, the model showed SE followed by EUE of highest importance for explaining yield variability in all three nutrient management practices.

Across years, the measured grain yield of maize ranged from 4.1 to

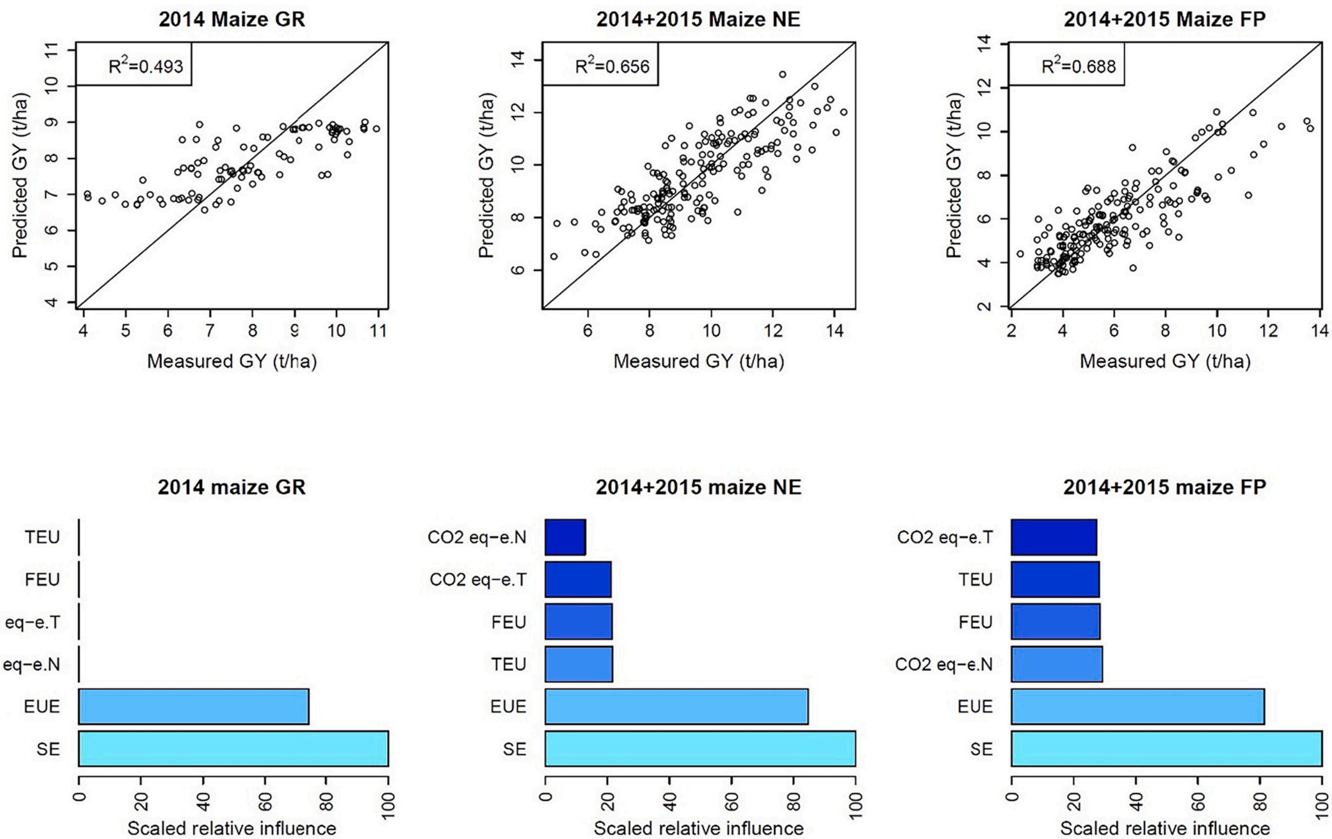

Fig. 5. Measured vs. predicted maize grain yield under Government recommendation (GR), Nutrient Expert recommendation (NE) and Farmers' practice (FP) using random forest model (*Upper row with three quadrants*), and variables explaining yield variability (*Lower row with three quadrants*) in the EIGP of Nepal. Fig. 3 for the detailed explanation of figure labels.

11.0 t ha^{-1} in GR, from 4.9 to 14.3 t ha^{-1} in NE, and from 2.3 to 13.6 t ha^{-1} in FP (Fig. 5). The OOB R^2 for maize was highest (0.68) for FP while it was lowest (0.49) for GR. Following the similar trend as in wheat, SE followed by EUE appeared as the most influential variable for explaining yield variability under all nutrient management practices. While this is an important finding, to our knowledge there is no literature supporting such results for all studied crops. We suggest that further research be conducted to advance the scientific knowledge on how SE and EUE can be major predictors for explaining cereal yields variability using the machine learning approaches.

The negative correlations between GHGI and grain yield (−0.95 rice, −0.64 wheat, and − 0.62 maize) indicate that a reduction in GHGI is possible with increasing yield in all cereals. Similar to our study, other studies have also found that higher yields can be achieved with minimal yield-scaled GWP by optimizing N application rates (Pittelkow et al., 2014; Sainju et al., 2014a, 2014b; Devkota et al., 2019). However, the current study as well as these studies used only bio-physical and not the socio-economic indicators to explain yield variability. We recognize the importance of socio-economic factors for determining the input use by the smallholders, and the usefulness of partial dependence plots in explaining yield response to inputs (Dutta et al., 2020; Devkota et al., 2020; Paudel et al., 2020). We didn't consider these two aspects in the current analysis due to limitations of technical and financial resources. We recommend that future research include analysis using the socio-economic factors and the partial dependence plots to better predict and explain the yield variability and strengthen the applicability of RF in cereal production systems in Nepal and largely in the EIGP.

3.2. Energy-use efficiency and energy productivity

Energy-use efficiency (EUE) and energy productivity (EP) are commonly used in evaluating crop production systems considering the energy input and output. Higher EUE indicates higher energy output through grain plus straw compared to energy input through various production inputs while higher EP indicates lower energy use per unit of grain productivity. In this study, TEU through all sources was highest in NE and lowest in FP but the variability of TEU was higher in FP compared to NE (Fig. 6). Other researchers (Aravindakshan et al., 2015; Krupnik et al., 2015) have also reported the high proportion of TEU from fertilizer in Bangladesh. EUE in rice and wheat was higher ($p < 0.05$) in FP than in NE and GR, while in maize it was highest in GR (Table 2). Descending CDFs for individual nutrient management options, using data from each farmer and treatment, indicates the potential of increasing EUE or EP at a higher probability level (>80%) (Fig. 7). Across the treatments, EUE in rice ranged from 17.3 to 39, 16.5 to 40.4, and 8.0 to 124.5 while in wheat, it ranged from 2.8 to 18.5, 4.8 to 22.7, and 5.5 to 45.5, respectively in GR, NE, and FP. At all probability levels, FP had the highest, NE intermediate, and GR the lowest EUE in both crops. In maize, EUE ranged between 24.6 and 84.8, 12.3–65.9, and 7.7–141.3 in GR, NE, and FP, respectively. In 90% cases, GR had higher EUE than NE. In 30% cases, NE and FP had similar EUE, while in the remaining 70%, FP had higher EUE than in NE. The higher EUE in FP than in GR or NE (especially in rice and wheat) might be due to the motivational effect of training, as such practical training on improved and site-specific 4R nutrient stewardship was provided to farmers before and during the implementation of the trials.

Energy productivity (EP) behaved slightly differently to EUE; it was significantly higher under NE in wheat, FP in rice, and GR in maize (Table 2, Fig. 7). In rice, in 80% cases, EP was the same under NE and GR while in remaining 20%, it was higher under FP. In wheat, in 80% cases, EP was consistently higher under GR than NE while in remaining 20%, it was similar for both. FP had consistently lower EP than under NE or GR.

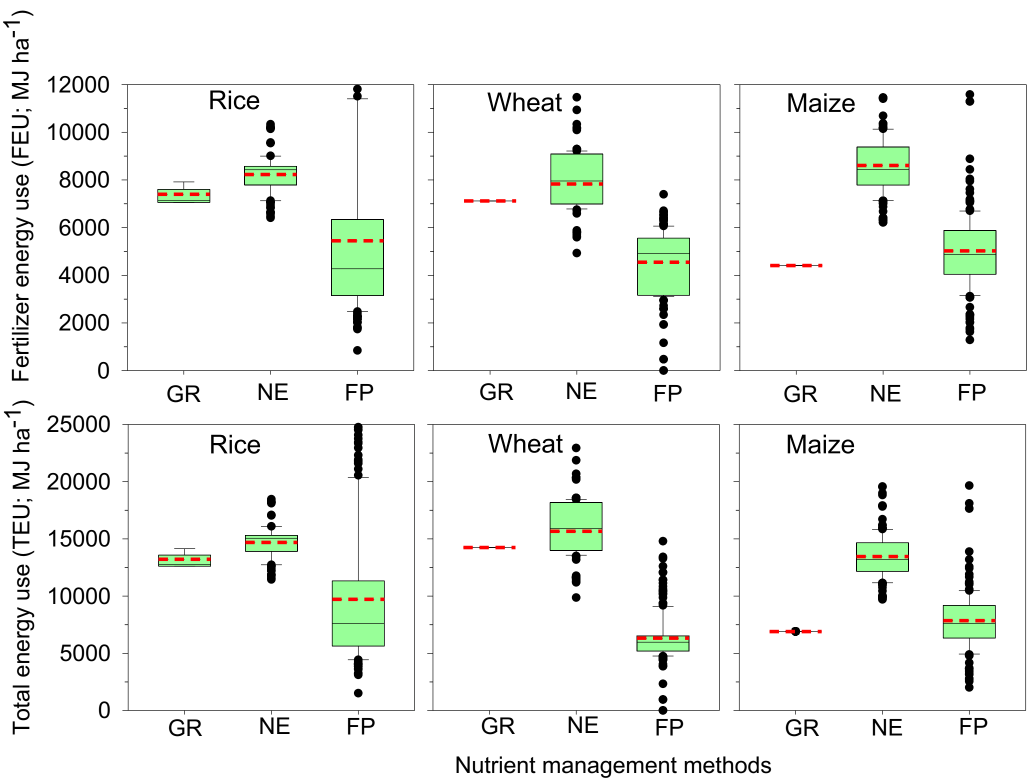

Fig. 6. Fertilizer energy use (MJ ha^{-1}) and total energy use (MJ ha^{-1}) for rice, wheat and maize as affected by three nutrient management methods in the EIGP of Nepal. The lower and the upper big solid dots are outliers, the error bars are minimum and maximum data point excluding outliers, the ends of the box are 25th and 75th percentiles and dotted and solid lines inside the box are means and medians, respectively. GR = Government recommendation, NE = Nutrient Expert recommendation, FP = Farmers' practice.

Table 2
Analysis of variance (ANOVA) showing yield (GY), greenhouse gas emission intensity (GHGI), fertilizer energy use (FEU), total energy use (TEU), specific energy (SE), energy productivity (EP) and energy-use efficiency (EUE) as affected by three nutrient management practices in rice, wheat and maize in the EIGP of Nepal.

Nutrient management	GY (kg ha^{-1})	GHGI (kg CO_2 eq. t^{-1} grain)	FEU (MJ ha^{-1})	TEU (MJ ha^{-1})	SE (MJ kg^{-1})	EP (kg grain MJ^{-1})	EUE
Rice							
GR	4398b	1212b	7399b	13212b	1.12a	0.33b	15.72b
NE	5037a	1078c	8226a	14689a	1.18a	0.35b	14.77b
FP	3722c	1388a	5461c	9752c	0.99b	0.53a	25.54a
P value	***	***	***	***	**	***	***
Wheat							
GR	2661b	490a	7119b	14238b	3.83c	0.19c	5.21b
NE	3428a	374b	7834a	15669a	5.66b	1.17a	2.83c
FP	2438c	324c	4598c	9749c	9.37a	0.82b	9.87a
P value	***	***	***	***	***	***	***
Maize							
GR	7889b	91c	4410c	6891c	0.43c	1.14a	39.47a
NE	9526a	128b	8607a	13448a	0.70a	0.72c	24.90c
FP	5997c	144a	5026b	7854b	0.64b	0.87b	30.98b
P value	***	***	***	***	**	***	***

** Significant at $p < 0.01$ and *** Significant at $p < 0.001$.

In maize, there was 50% probability of higher EP under NE and 50% under FP; at all probability levels, GR had the lowest EP. These results show that for increased EUE or EP, the lowest fertilizer rates often seem to be the best. Further, there is a trade-off between EUE and the fertilizer rates, and hence the optimization of the EUE might be needed for encouraging farmers to apply fertilizers (either organic or inorganic) for achieving the sustainability of the cereal production systems. Higher EUE in FP was achieved due to lower energy output and lower TEU than in NE or GR. Similarly, higher EP was achieved in NE because of higher grain and straw yields though it used lower TEU than in GR or FP. Variations in TEU, EU and EP could also be attributed to variations in soil and climate (Gathala et al., 2016, 2020).

Rahman and Rahman (2013) reported EUE and EP of 7.07 and 0.28 for maize grown in Bangladesh while Gathala et al. (2020) obtained average EUE and EP of 16.5 and 0.42 respectively for maize grown after rice across eight districts in Bangladesh, Nepal Terai and eastern India in the EIGP. The values for both parameters in both studies were much lower than the EUE and EP of 12.3–124.3 and 0.3–3.0, respectively,

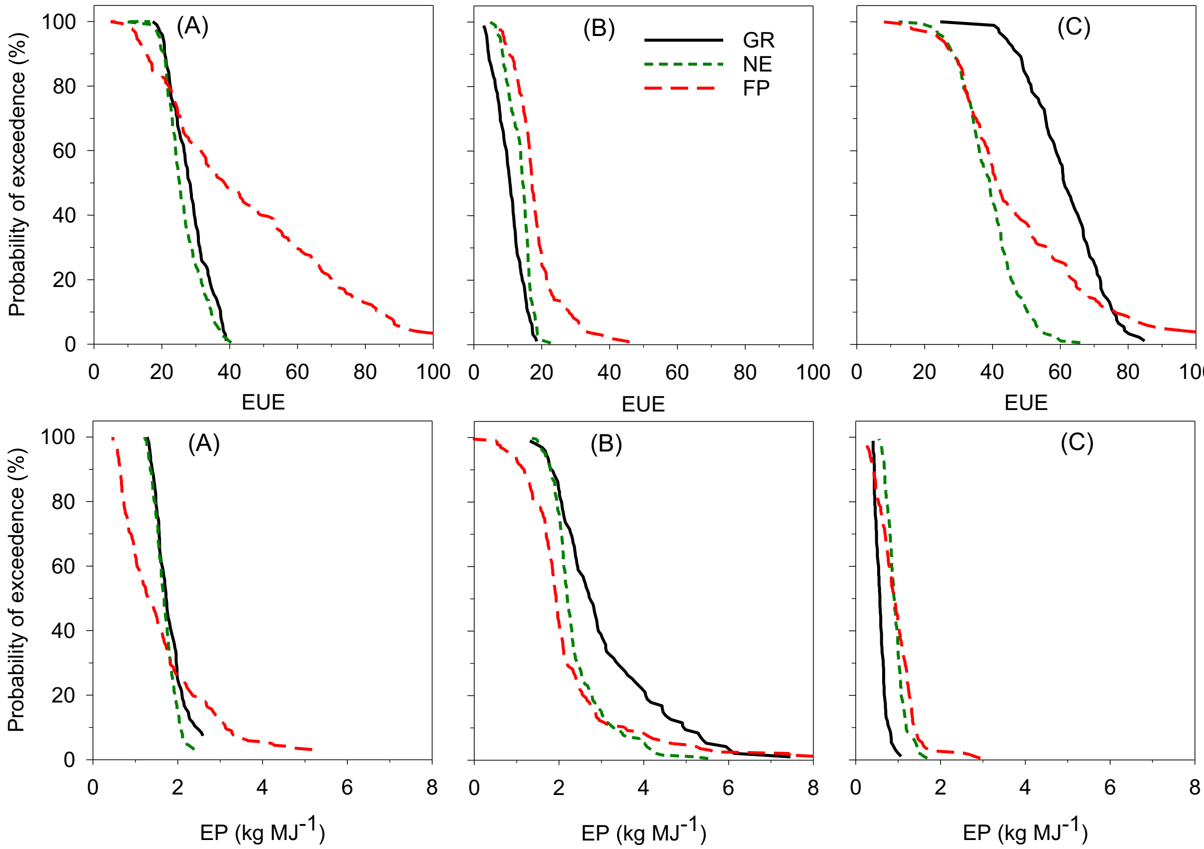

Fig. 7. Cumulative density functions for (i) energy-use efficiency (EUE) for rice (A), wheat (B), and maize (C) (*Upper row*) and (ii) energy productivity (EP) for rice (A), wheat (B), and maize (C) (*lower row*) as affected by three nutrient management methods in the EIGP of Nepal. GR = Government recommendation, NE = Nutrient Expert recommendation, FP = Farmers' practice.

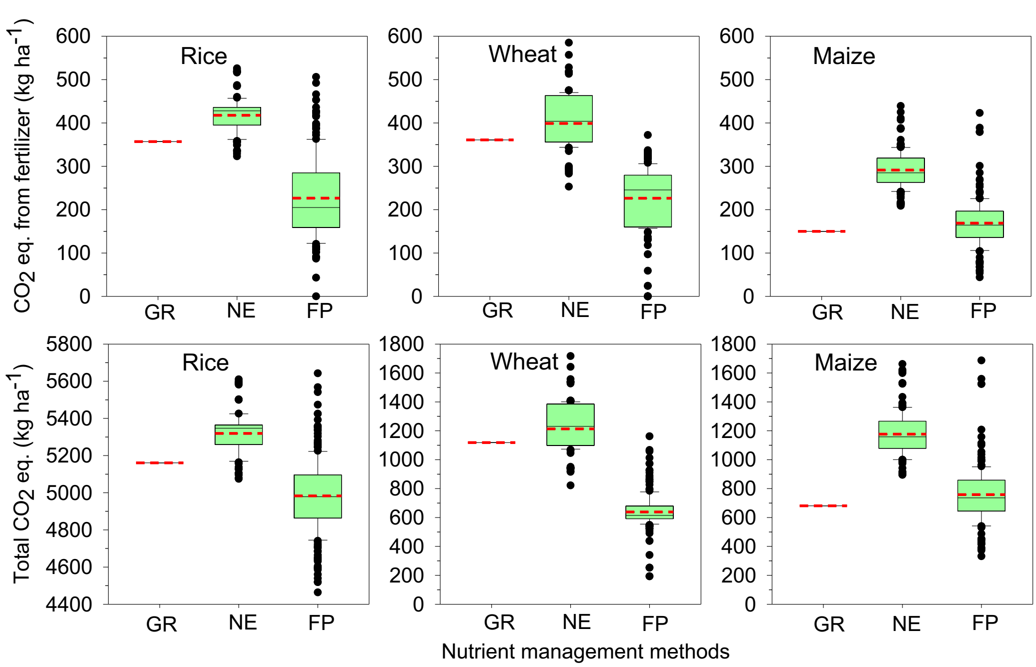

Fig. 8. CO_2 equivalent emissions from fertilizer use and total CO_2 equivalent emissions from various sources (kg ha^{-1}) from rice, wheat and maize as affected by three nutrient management methods in the EIGP of Nepal. The lower and the upper big solid dots are outliers, the error bars are minimum and maximum data point excluding outliers, the ends of the box are 25th and 75th percentiles and the dotted and solid lines inside the box are means and medians, respectively. GR = Government recommendation, NE = Nutrient Expert recommendation, FP = Farmers' practice.

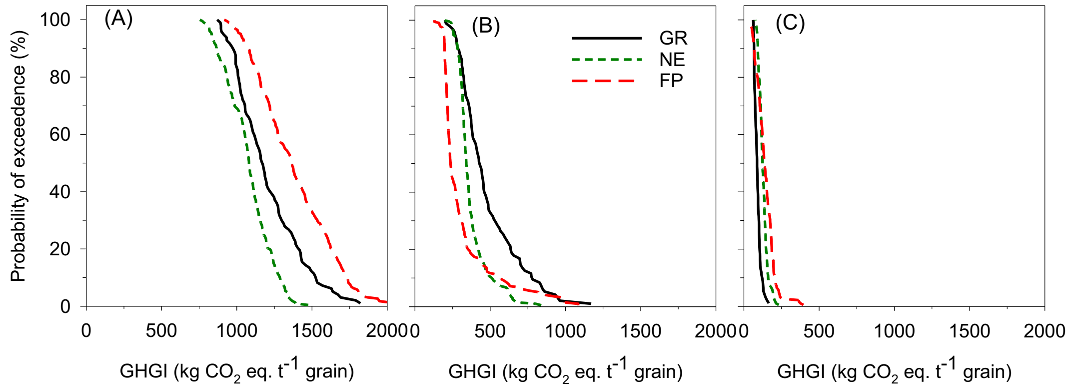

Fig. 9. Cumulative density functions for greenhouse gas intensity (GHGI) for rice (A), wheat (B), and maize (C) as affected by three nutrient management methods in the EIGP of Nepal. GR = Government recommendation, NE = Nutrient Expert recommendation, FP = Farmers' practice.

obtained in the current study. For rice across rice-maize, rice-wheat, and rice-lentil systems in the EIGP, EUE was 15.8 and EP was 0.40 while for wheat they were 8.7 and 0.22 respectively (Gathala et al., 2020). The EUE and EP for both crops in our study were much higher than those reported by Gathala et al. (2020). Such differences in EUE and E*P* values for all crops between the other studies and our study were due to differences in energy input and output. The study by Rahman and Rahman (2013) was based on survey data from various locations in Bangladesh differing in soils and climate. Gathala et al. (2020)'s results were based on on-farm trials from eight districts in the EIGP while results for the current study were from 600 on-farm trials from only two eastern Terai districts of Nepal.

3.3. *Greenhouse gas emission intensity*

The GHGI is related to GWP due to crop production. A positive GHGI indicates a net source while a negative GHGI indicates a net sink of GHGs in the soil. In this study, the highest GHGI was found in rice followed by wheat and maize (Table 2). Higher GHGI in rice was mostly attributed to puddling and flood water adopted as the predominant water management practice in rice (IPCC, 2019). CO_2-eq. emissions from fertilizers were higher in maize than in rice or wheat due to higher fertilizer rates and other agrochemicals, and irrigation water, which was mostly attributed to higher fertilizer application in NE than in FP. However, variability of CO_2 eq. emission was higher in FP compared to

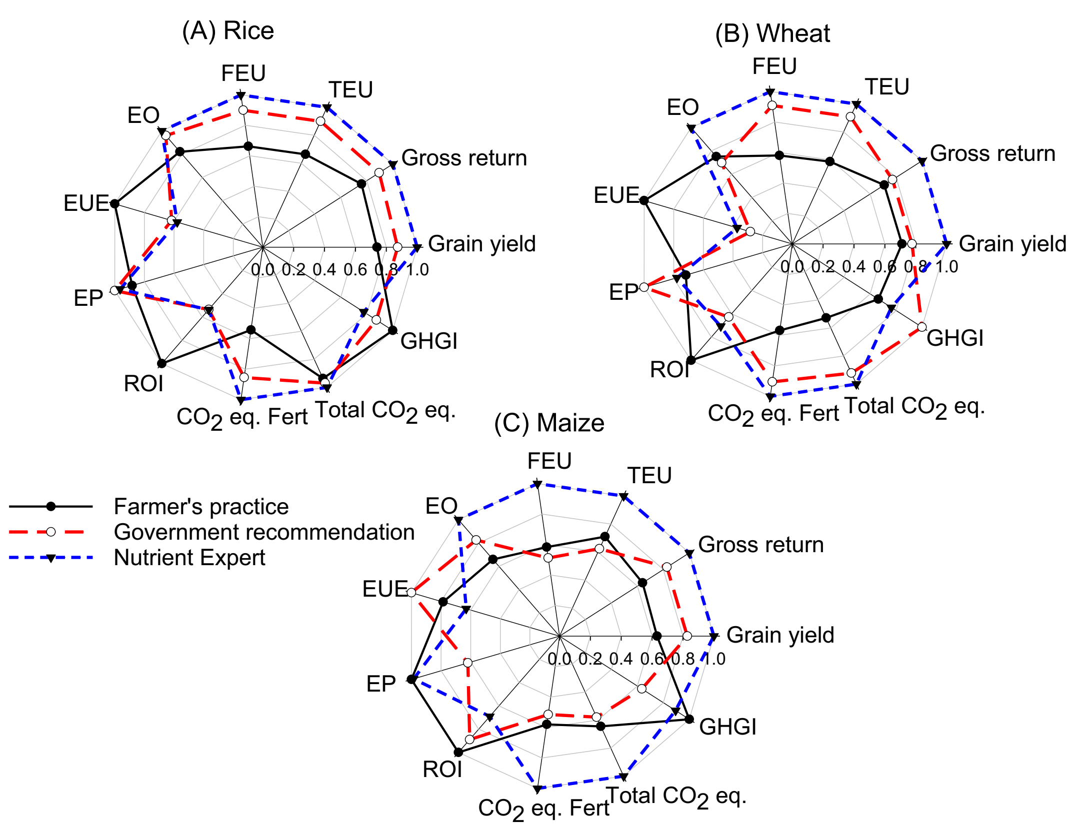

Fig. 10. Multi-criteria assessment with various economic, energy, and environmental indicators across three nutrient management practices for the smallholders in the EIGP of Nepal. TEU = Total energy use (MJ ha^{-1}); FEU = Fertilizer energy use (MJ ha^{-1}); EO = Energy output (MJ ha^{-1}); EUE = Energy-use efficiency; EP = Energy productivity (kg MJ^{-1}); CO_2 eq. Fert. = CO_2 equivalent emission from fertilizer applied (kg ha^{-1}); Total CO_2 eq. = Total CO_2 equivalent emission (kg ha^{-1}); GHGI = Greenhouse gas emission intensity.

NE (Fig. 8).

The CO_2 eq. emissions were variable across the nutrient management options in each crop. Comparing across the treatments, GHGI in rice ranged from 754 to 2201 kg CO_2 eq. emission t^{-1} of grain produced, with 870 to 1822, 754 to 1475, and 916 to 2201 respectively for GR, NE, and FP (Fig. 9). At all probability levels, FP had consistently the highest while NE had the lowest GHGI (Table 2, Fig. 9). The patterns were different for wheat and maize than for rice. GHGI in wheat ranged from 199 to 1172 kg CO_2 eq. emission t^{-1} of grain produced in GR, from 191 to 839 in NE, and from 129 to 1085 in FP. GR had consistently the highest while FP (80% cases) had the lowest GHGI. In maize, GHGI ranged from 62 to 166 kg CO_2 eq. emission t^{-1} of grain produced in GR, 75 to 232 in NE, and 43 to 396 in FP. In about 80% cases, FP had higher GHGI than NE and in most cases, GR had lower GHGI than the other two treatments. These results indicate that NE-based management in rice can clearly result in lower GHGs t^{-1} of grain produced compared to GR or FP. In the other two crops, GHGs emissions with NE-based fertilizer recommendations were in between FP and GR. Our results reveal that though NE recommended optimum fertilizer rates for all crops, the recommendation was generally higher than used by farmers (FP), which lead to higher CO_2 emissions. Other studies have also reported that the emissions of key GHGs, in particular nitrous oxide and methane, will be high with increased use of fertilizer N (Tilman et al., 2001; Snyder et al., 2009; Woods et al., 2010). Our results are also consistent with Devkota et al. (2019), Sainju et al. (2014a, 2014b) and Pittelkow et al. (2014) who all reported that YSE or GHGI can be decreased with optimal fertilizer rates.

Gathala et al. (2020) reported mean CO_2-eq. emissions (t CO_2 eq-emissions ha^{-1}) of 0.65, 0.76 and 1.06 in rice, wheat, and maize in eight districts of the EIGP varying in soil, climate and farmers' management practices. In the current study, CO_2-eq. emissions (kg CO_2 eq. emissions t^{-1} grain produced) in rice ranged from 754 to 2201, in wheat from 129 to 1172, and in maize from 43 to 396. Differences between these studies are due to differences in soil, climate, and management practices.

3.4. Multi-criteria assessment of nutrient management options

A holistic multi-criteria assessment of productivity, profitability, energetics, CO_2-eq. emissions, and GHGI comparing the three nutrient management options for all three crops using the radial 'spider' diagrams (Snapp et al., 2010) showed NE-based recommendation was better than the GR or FP in terms of crop yield, total gross returns and ROI, and energy output (Fig. 10). The NE recommendation, however, used the highest amount of total energy and energy from fertilizer and emitted the highest amount of CO_2-eq. emissions through fertilizers in all crops. This resulted in lower EUE by 63%, 42% and 16% under NE compared to FP in wheat, rice, and maize, respectively. The highest productivity and profitability in all crops together with the lowest GHGI in rice and wheat and moderate GHGI in maize indicate that NE-based fertilizer recommendation can increase both yield and profit while reducing GHGI.

3.5. Policy implications and conclusions

This research, conducted on 600 trials with three major cereal crops across two Terai districts of Nepal in the EIGP of South Asia, demonstrated the importance of measuring YSE or GHGI to evaluate the performance of different nutrient management options. We conclude that although NE-based recommendations used slightly higher fertilizer rates in all cereals, the increased yield, profit, and energy productivity, and reduced GHGI compared to GR or FP compensated for the increased fertilizer use. This has important implications for farmers, policymakers, and stakeholders to scale-out the NE DSS tool for its wider uptake not just in Nepal but more broadly across smallholder farmers practicing cereal production systems in all three countries of the EIGP. Quantifying the EP or GHGI provides evidence for policymakers and other stakeholders to make policy decisions and scale-out the NE-based fertilizer recommendations in all the countries of the EIGP.

This study also concludes that the machine learning approach (Random Forest) can determine the relative importance and performance of energy and environmental indicators in predicting and explaining the yield variability of major cereal crops. Random Forest showed SE as the major predictor of grain yield in all cereals followed by EUE. Yield-scaled emissions approach of evaluating GHGs emissions showed that with NE-based recommendation, it is possible to achieve the lowest GHGI in all cereals. This was particularly true for rice, which has a higher level of productivity and profitability, but also is the highest emitter of GHGs. The current farmers' practices have higher EUE and low crop yields due to the use of low fertilizer rates, particularly in rice and wheat. Cereal yields with such low fertilizer rates will not be enough to meet the increasing food requirement in the context of the growing population in Nepal and the EIGP.

There are some caveats and uncertainties in the estimations of GHGs emissions and energy use since these were not direct measurements, rather they were based on the coefficients used in the literature. Hence, improvements in GHGI measurements or predictions could further reduce yield-scaled GHGs emissions through NE-based recommendations compared to GR and FP. We recommend that the Nepal government consider developing dissemination pathways for increasing the adoption and scaling-out of NE-based agro-advisory DSS tools. Further research on site-specific in-situ measurements of energy use and GHGs emissions should be conducted for further validation of NE-based recommendations and machine learning approaches to facilitate their wider adoption and out-scaling.

Declaration of Competing Interest

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

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