CrossMark

CAMBRIDGE
UNIVERSITY PRESS

RESEARCH ARTICLE

A data-mining approach for developing site-specific fertilizer response functions across the wheat-growing environments in Ethiopia[‡]

Wuletawu Abera[1,]*[ⓘ], Lulseged Tamene[1], Kindie Tesfaye[2], Daniel Jiménez[3,4], Hugo Dorado[3], Teklu Erkossa[5], Job Kihara[6], Jemal Seid Ahmed[7,9], Tilahun Amede[8] and Julian Ramirez-Villegas[3,10,11]

[1]International Center for Tropical Agriculture (CIAT), Addis Ababa, Ethiopia, [2]International Maize and Wheat Improvement Center (CIMMYT), Addis Ababa, Ethiopia, [3]International Center for Tropical Agriculture (CIAT), c/o Bioversity International, Rome, Italy, [4]Universidad Icesi, Calle 18 # 122-135, Pance, Cali, Valle del Cauca 760031, Colombia, [5]Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ), Addis Ababa, Ethiopia, [6]International Center for Tropical Agriculture (CIAT), Nairobi, Kenya, [7]Ethiopia Institute of Agricultural Research (EIAR), Addis Ababa, Ethiopia, [8]International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), Addis Ababa, Ethiopia, [9]Scuola Superiore Sant'Anna, Pisa, Italy, [10]Bioversity International, Rome, Italy and [11]Plant Production Systems Group, Wageningen University & Research, Wageningen, The Netherlands
*Corresponding author. Email: wuletawu.abera@cgiar.org

Summary

The use of chemical fertilizers is among the main innovations brought by the 1960s Green Revolution. In Ethiopia, fertilizer application during the last four decades has led to significant yield gains, yet yield remains below its potential across much of the country. One of the main challenges responsible for low yield response to fertilizer application has been the use of 'blanket' recommendations, whereby no tailoring of fertilizer amount and frequency is done based on soil requirements. As a result, the amount of fertilizer applied ranges widely, and can be either sub- or supra-optimal. There is thus an increasing need for site-specific fertilizer recommendations which take into account site characteristics such as climate variables (temperature, rainfall, and solar radiation); soil factors (soil organic carbon, moisture, pH, texture, cation exchange capacity, and level of macro- and micronutrients); and topographic position indices. This article reports on a data-mining approach we developed on a large dataset of 6585 wheat (*Triticum aestivum*) field trials. The dataset includes detailed, site-specific biophysical variables to create nutrient response functions that can guide optimal site-specific fertilizer application. The approach used a machine-learning model (random forest) to capture the relationship between nutrients – nitrogen (N), phosphorous (P), potassium (K), and sulfur (S) – and wheat yield. The model explained about 83, 82, 47, and 69% of variances of yield for N, P, K, and S omission, respectively, with consistent performance across training and testing datasets. Expectedly, for N and P omission data, the most important explanatory variables are nutrient rate, followed by soil organic carbon and soil pH. For K and S, however, climatic variables played an important role alongside nutrient rates. The site-specific yield–fertilizer response curves derived from our model are highly variable from location to location, as they are affected by the climatic, soil, or topographic conditions of the site. Importantly, using principal component analysis, we showed that the shape of the fertilizer response curves is a result of the multiple environmental factors (including soil, topography, and climate) that are at play at a given site, rather than of a specific dominant one. The research output is expected to respond to the national policy demands for a sound method to identify the optimal fertilizer rate to increase economic returns of fertilizer investments and take fertilizer utilization research one step further.

Keywords: Site specific; Fertilizer recommendation; Fertilizer response curves; Wheat yield

---

[‡]The original version of this article was published with incorrect funding information. A notice detailing this has been published and the errors rectified in the online PDF and HTML version.

Introduction

The global population is expected to reach 9.7 billion and the associated global demand for food is expected to roughly double by 2050 (Koning and van Ittersum, 2009). Although this will create demand for an additional 593 million hectares of land to feed the increasing population, the potential to acquire such land is very slim (Searchinger *et al.*, 2019). Hence, the most feasible option is to sustainably improve overall system productivity on current arable land. The use of adequate and appropriate inputs is a critical entry point to sustainably intensify production and tackle food insecurity, undernutrition, and poverty (Garnett *et al.*, 2013; Vanlauwe *et al.*, 2014). The use of improved agronomic practices, including the application of macronutrients, resulted in an unprecedented increase in crop yield during the 1960s Green Revolution (Otsuka and Larson, 2012; Khush, 2001).

Compared with other regions, the situation in Africa is more complex as both input supply and market access are limited, and the ability of farmers to apply the required inputs is low. Although the crop production potential of Africa is large under optimal agronomic management conditions (Tittonell and Giller, 2013), yield gaps are one of the largest (van Ittersum *et al.*, 2016) due to poor soil fertility (Chianu *et al.*, 2012; Stewart *et al.*, 2020), erratic rainfall (Fei *et al.*, 2020; Li *et al.*, 2015), and poor agronomic practices (Kalra *et al.*, 2007; Moswetsi *et al.*, 2017) among others. Consistent with this, the application of fertilizer in sub-Saharan Africa (SSA) is one of the lowest (8 kg/ha) when compared with South-East Asia (200 kg/ha), Europe (110 kg/ha), Latin America (95 kg/ha), and North America (107 kg/ha) in 2010 (Wanzala and Groot, 2013). In Ethiopia, the focus of this study, productivity is still well below its potential despite efforts to increase the use of fertilizer and improved seed for many crops. One of the main challenges in Ethiopia, as elsewhere in SSA, is the high variability in environmental, social, and other factors that determine the adoption of and response to seed and fertilizer inputs (Spielman *et al.*, 2010) and agronomic practices (Kassie *et al.*, 2009; Marenya *et al.*, 2020). It is thus important to understand the spatio-temporal dynamics of production conditions and the types and amounts of inputs required for farmers to use in their fields.

One of the challenges in Ethiopia (and elsewhere) is the widespread use of 'blanket' recommendations – whereby a single fertilizer rate is prescribed for a large area or across the entire country. This approach can lead to either a zero or negative yield response to fertilizer, and generally low profitability from the fertilizer use (Kihara *et al.*, 2016; Vanlauwe *et al.*, 2011). Site-specific fertilizer application can thus constitute an effective means to address low crop response to fertilizers and seed inputs as well as to reduce the overall environmental impact due to inorganic fertilizer pollution in agricultural landscapes (Kihara *et al.* 2020; Rodriguez, 2020). Many factors, ranging from topography, climate (e.g. Getnet *et al.*, 2015), availability of nutrients in the soil (Kihara and Njoroge, 2013), soil catena (Thelemann *et al.*, 2010), landscape position (Amede *et al.*, 2020), and soil moisture regime (Getnet *et al.*, 2015) determine crop response to fertilizers.

Given the low agronomic effectiveness and poor economic efficiencies of blanket fertilizer applications, some efforts have already been made to improve such recommendations. For example, Optimizing Fertilizer Recommendations for Africa (OFRA) developed an agro-ecological zone (AEZ)-based fertilizer recommendation for Ethiopia using data from a few sites (Kaizzi *et al.*, 2017). And though the AEZ-based approach provided relatively refined fertilizer recommendations, it did not take into account the several micro-factors that influence crop response to nutrients, and hence still results in a coarse recommendation that can lead to sub- or supra-optimal fertilizer applications for farmers. Amede *et al.* (2020) showed the effect of local-scale topography on yield response to fertilizer, and developed a topography-based fertilizer recommendation. However, this approach, too, has ignored other important sources of fertilizer response determinants and hence is not suited for holistic, site-specific fertilizer recommendations. Another effort on disaggregated fertilizer recommendation is the recent soil fertility map developed under the EthioSIS project[1]. EthioSIS developed a nutrient recommendation map based on the level of nutrients in the soil. However, data show that many areas can still be non-responsive to fertilizer application due to a specific nutrient with the low amount in

the soil (Tittonell *et al.*, 2007). Thus, identifying existing nutrient pools in the soil alone is not enough to provide reliable fertilizer recommendations as nutrient uptake is influenced by soil and non-soil related factors. None of the methods mentioned above consider the influence of relevant soil, climate, topographic, and soil-nutrient pool in an integrated manner.

In this study, we demonstrate a site-specific fertilizer recommendation approach based on a fertilizer-yield response function for wheat in Ethiopia. Wheat was chosen because it is a key staple crop grown by 4.7 million farmers, and because of its reported large yield gaps; that is, yield is only about 20% of its potential (Silva *et al.*, 2019; van Ittersum *et al.*, 2016). The novel approach included: (1) a machine-learning (ML) model to identify the most important site-specific variables determining wheat yield based on data collated from various sources; (2) the generation of spatially distributed nutrients—nitrogen (N), phosphorous (P), potassium (K), and sulfur (S) – response curves for wheat; and (3) the identification of the biophysical optimal nutrient recommendation for wheat. In the last one decade, the application of ML to guide agronomic management decisions has been increasing in many parts of the world (Chlingaryan *et al.*, 2018). Unlike process-based crop models which depends on limited and defined input–output functions, ML method 'learns' to develop any form of transfer functions to predict output based on the provided inputs (Jeong *et al.*, 2016; Shahhosseini *et al.*, 2019). In addition, they have the capability to integrate large and ever increasing *in situ*, remote sensing and other legacy data, and handle non-linear tasks to make the best-informed decisions towards site-specific nutrient management (Chlingaryan *et al.*, 2018; Jeong *et al.*, 2016). The approach implemented here adds to the development of decision support tools that can contribute to the sustainable intensification of African cropping systems.

Materials and Methods

Study area

Our study focuses on Ethiopia, a major wheat-growing country in the Horn of Africa and the largest wheat producer in SSA. Wheat is grown across the diverse landscapes in the mid- and highlands of the country ranging from 1800 to 3800 m asl (Figure 1). Wheat is selected for this case study because of its importance as a food security crop in the country and its wide adoption throughout larger areas of Ethiopia (Hodson *et al.*, 2020). Wheat is grown by more than 4.7 million farmers on approximate 1.6–1.8 million hectares of land, or about 15–18% of the total cropland of the country (CSA, 2016; Hodson *et al.*, 2020; Minot *et al.*, 2019). Currently, wheat is produced mostly under rainfed conditions and with relatively low inputs (Anteneh and Asrat, 2020).

Yield response to fertilizer dataset

The agronomic dataset used for the modelling was collected from various sources in Ethiopia. Several researchers and institutions in Ethiopia have been conducting agronomic fertilizer-yield trials across the wheat-growing areas since the 1960s (Zegeye, 2001). We compiled agronomic data from various existing sources, namely: (1) published data from peer-reviewed scientific journals (Kihara *et al.*, 2017); (2) the OFRA database (EIAR, 2020); and (3) Ethiopia Institute Agricultural Research (EIAR) trials data from sites that are coordinated both at regional state and federal levels. The combined dataset constitutes a total of 6585 agronomic experiments (with 179 unique locations) conducted in a wide range of wheat-growing environments of Ethiopia between 1986 and 2017. The data cover almost all wheat-growing areas in the central highlands of Ethiopia (Figure 1). The established database was primarily for nutrient omission trials for N, P, K, and S. For each trial, the district and location (latitude and longitude) of the trials, treatment type (i.e. nutrient type), nutrient application rate, resulting yield, and year of a trial conducted variables are reported. A normalized response ratio of yield, which is calculated as yield of the
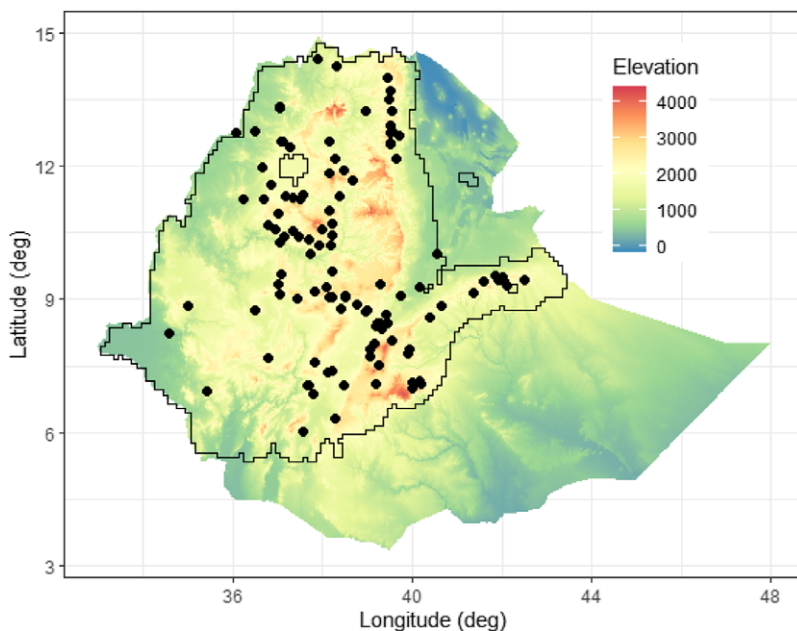
Figure 1. Study area (wheat-growing area of Ethiopia in polygon) and the location of data points (point) used in this study.

treatment divided by the yield of the control for each location, is used for model crop yield response to nutrients.

Environmental covariates

To model the response of wheat yield to fertilizer, we included climate variables such as rainfall, temperature, and solar radiation; topographic variables (elevation and topographic index); and soil factors, particularly soil organic carbon (SOC), soil pH, soil texture, and cation exchange capacity (CEC). As climatic elements are very dynamic and their variabilities are strongly associated with yield variabilities (Hoffman *et al.*, 2018), we used monthly rainfall, maximum and minimum temperature, and solar radiation data for the first four months of the growing season in the modelling.

We downloaded climate data from the TerraClimate database (Abatzoglou *et al.*, 2018). TerraClimate is a global monthly database of 2.5 arc-min (~4 km) spatial resolution that covers the period 1958–2019. TerraClimate is developed by combining high spatial resolution (30 arc-sec) average climatology data from WorldClim (Fick and Hijmans, 2017) and the monthly temporal resolution data from CRU TS4.0 and the Japanese Reanalysis (JRA-55). The combination of these datasets then produces a dataset with greater temporal resolution than WorldClim, and greater spatial detail than CRU TS4.0 and JRA-55. We extracted monthly precipitation, maximum and minimum temperature, and solar radiation data for each of the trials using their geographic coordinates and reported growing seasons.

Soil data were downloaded from the 250-m spatial resolution SoilGrids database (Hengl *et al.*, 2017). SoilGrids is a pan-Africa database constructed by applying random forest (RF) modelling to more than 28 000 individual soil sampling locations and many geospatial covariates. Using the point locations of the wheat trials, we extracted the organic carbon content, pH, clay percentage, silt percentage, and CEC as key variables that potentially influence the fertilizer response of wheat. Finally, topographic variables (i.e. the elevation and the topographic position index) were obtained

Table 1. List of covariates (their sources and their spatial resolution) used in the ML modelling

Variable	Specific variables used	Sources	Spatial resolution	References
Precipitation	June precipitation (Rain_1), July precipitation (Rain_2), August precipitation (Rain_3), Sept precipitation (Rain_4)	TerraClim (TerraClimate - Climatology Lab)	~4 km	Abatzoglou *et al.*, 2018
Maximum temperature	June Temp_max (Tmax-1), July Temp_max (Tmax-2), August Temp_max (Tmax-3), Sept Temp_max (Tmax-4),	TerraClim (TerraClimate - Climatology Lab)	~4 km	Abatzoglou *et al.*, 2018
Minimum temperature	June Temp_min (Tmin-1), July Temp_min (Tmin-2), August Temp_min (Tmin-3), Sept Temp_min (Tmin-4),	TerraClim (TerraClimate - Climatology Lab)	~4 km	Abatzoglou *et al.*, 2018
Solar radiation	June SolarRad (Srad_1), July SolarRad (Srad_2), August SolarRad (Srad_3), Sept SolarRad (Srad_4)	TerraClim (TerraClimate - Climatology Lab)	~4 km	Abatzoglou *et al.*, 2018
Soil covariates	Carbon (SOC), pH (pH), Clay percentage (Clay_%), Silt percentage (Silt_%), Cation exchange capacity (CEC)	ISRIC SoilGrid (SoilGrids250m 2.0)	250 m	Hengl *et al.*, 2017
Topographic covariates	Elevation Topographic position index (TPI)	SRTM (SRTM 90m Digital Elevation Database v4.1 – CGIAR-CSI)	90 m	Jarvis *et al.*, 2008

from the void-filled Shuttle Radar Topography Mission (SRTM) database at 90 m spatial resolution (Jarvis *et al.*, 2008). The full list of environmental factors (covariates) used in the ML model is presented in Table 1.

Actual yield prediction using machine learning

The fundamental formulation of yield at any given location can be expressed as the function of genotype, environment, and agronomic management as follows:

$$Y_A = f(G \times E \times M) \tag{1}$$

where Y_A is the actual yield response ratio (i.e. yield normalized by control experiment at a given location), G is the crop varieties grown, E is site-specific environmental variables, and M is agronomic management practices applied at a given plot. To capture site-specific yield prediction and understand fertilizer response, we included several environmental factors that are important to determine yield in the 'E' term (Table 1). The 'M' term is the chemical fertilizer rate reported in the trial database.

To model Y_A, we used a ML algorithm as it allows constructing a non linear relationship between the response and the predictor variables. We selected the RF model because of its relatively robust performance in capturing collinearity among predictor variables and noisy covariate data, in addition to its comparatively better performance concerning other ML tools (Breiman, 2001; Svetnik *et al.*, 2003). In the RF model, data were split into training (70% of the data) and testing (30%) components for building the model and model testing, respectively (Svetnik *et al.*, 2003).

The model building followed a stepwise procedure starting from all potential variables that can explain yield response, then dropping those variables that do not show variability and do not improve model performance. The variable of importance is computed based on the accuracy of the model performance (particularly mean square error (MSE)) computed on the out-of-bag data for each tree, and then the same computed after permuting a covariate. The differences are averaged and normalized by the standard error. Then the order of importance of the variable is based on the mean decrease in accuracy of the model (i.e., MSE). Towards this aim, we used the variable selection method using the CART R package (Kuhn, 2008). The RF model is optimized for the number of trees (ntree) to grow and the number of predictors used at each node (mtry). In this study, several values were considered for the mtry parameter, varying from 2 to the whole number of predictors (Kuhn and Johnson, 2013). To assess the performance of the model between predicted and observed yield in both the training and testing datasets, R^2 and the Willmott Index of Agreement (d) (Willmott *et al.*, 1985) were used.

A site-specific fertilizer response function

While Eq. 1 provides yield response prediction at any given location based on site-specific inputs, disentangling the impact of fertilizer application rate on yield from the rest of the parameters can be done using a partial dependence plot and Individual Conditional Inference (ICE). Many studies have used partial dependence analysis (Cutler *et al.*, 2007; Friedman *et al.*, 2001) to estimate the average partial effect of one or more variables on the outcome of the ML model—in this case yield (Delerce *et al.*, 2016; Jiménez *et al.*, 2019). Partial dependence plots show the general trend between the model output and target variable, whether it is linear, monotonic, or complex. However, this analysis assumes that other values are kept constant at the average value, and hence the result cannot be used for real yield response to fertilizer application and cannot be disentangled for a specific location. In this study, we used the ICE (Goldstein *et al.*, 2015) method to analyze fertilizer responses at any specific location by varying fertilizer application rate under the prevailing condition of other environmental factors, which helps generate fertilizer response curves at any given location. ICE estimates the predicted response as a function of a target variable, $Fert_{Rate}$, conditional on some observed covariates (G, E, M). Mathematically, it can be expressed as in Equation 2.

$$Y_a(Fert_{Rate}) = \frac{\partial \, Y_a f(G \times E \times Fert_{Rate})}{\partial Fert_{Rate}} \tag{2}$$

where f ($G \times E \times Fer_{Rate}$) is an estimated yield based on a trained RF model. And although we focus specifically on fertilizer response curves, Equation 2 can be applied to evaluate the relationship of other environmental variables with yield. For each response curve, or any location with a response curve developed, the biophysical optimal nutrient can be identified as the fertilization level that corresponds to the highest yield (yield response ratio). This is not related to agronomic or economic optimal nutrient recommendation.

We then grouped the fertilizer response curves into three categories based on the lower, middle, and upper quartile ranges of the slope of the curves. Accordingly, the three response curve groups represent low, medium, and high nutrient responsive areas. We applied a principal component analysis (PCA) to categorize the environmental variables that determine the nutrient response groups. In all cases, we retain the three first principal components (PCs) as these have the largest contribution to total explained variance in the PCA.

Table 2. Goodness of fit for the training and testing datasets and parameters of the random forest model for N, P, K, and S omission trials (d = index of agreement)

Indices	N (n = 1911)		P (n = 1934)		K (n = 1869)		S (n = 817)	
	Training	Evaluation	Training	Evaluation	Training	Evaluation	Training	Evaluation
R^2	0.73	0.73	0.77	0.78	0.47	0.48	0.48	0.43
d	0.89	0.90	0.91	0.93	0.79	0.79	0.76	0.73
mtry	16		20		22		12	
Splitrule	maxstat		maxstat		maxstat		maxstat	
min.node.size	20		40		50		2	

Results

Model performance

The RF model generally performed well at predicting yield response to nutrients, with N and P showing the greatest model performance, and K showing the poorest performance (Table 2, Figure 2). The model optimization procedure produced optimal values of the RF model parameters (i.e. mtry, Splitrule, and min.node.size) with R^2 values ranging from 0.43 to 0.78 and index of agreement (d) values ranging from 0.73 to 0.93 both for the training and evaluation datasets (Table 2). The model performance results, particularly for N and P, could be considered very good, given the complexity of the yield estimation in a complex environment like the wheat-growing environments in Ethiopia. Notably, a greater number of well-distributed data points along the response range led to greater predictive skill since the response signal became stronger.

Importance of variables for yield response prediction

Figure 3 shows the importance of soil and climatic variables in predicting wheat yield under different rates of N, P, K, and S application rates. In all cases, fertilizer application rate was the most important variable in predicting yield, followed by some soil and climatic variables (Figure 3). Soil variables were the second and third most important compared with climate variables for N and P; the converse was true for K and S. Some variables (e.g. elevation, topographic features, and texture) have systematically low contributions to the model performance. However, the importance of the variables considered for model performance varied among the nutrients studied.

Crop fertilizer response

We assessed the relationship between nutrient level and yield using ICE (see subsequent section). Figure 4 shows both the average crop response for each nutrient response category and individual sites and individual years. The bold black curves for each category show that there is a monotonic increasing relationship between nutrient rate and yield response ratio for N, P, and S. On average, the crops are responsive to all nutrients, although primarily N and P show response ratios that vary strongly with the quantity of fertilizer used. The crop response curves to N and P have a similar shape with continuously increasing until it becomes flat, the average response to K and S is relatively flat (Figure 4). The spread across sites and years is considerably larger for K and S than for N and P. Some of the individual curves show shapes that do not comply with the established agronomic experiment studies. This could be due to some irregularities in the data generation process. Depending on the response curve gradients, the locations/areas are divided into three responsive categories: low, medium, and high (Figure 4). These suggest that in some sites and years, the response ratios vary strongly concerning the fertilizer applied, whereas in others the response ratios remain the same regardless of the fertilizer applied. In some cases, especially for K, response ratios decrease with increasing fertilizer amounts. This shows that the K application increases yield until a certain level, but the excessive application did not respond with
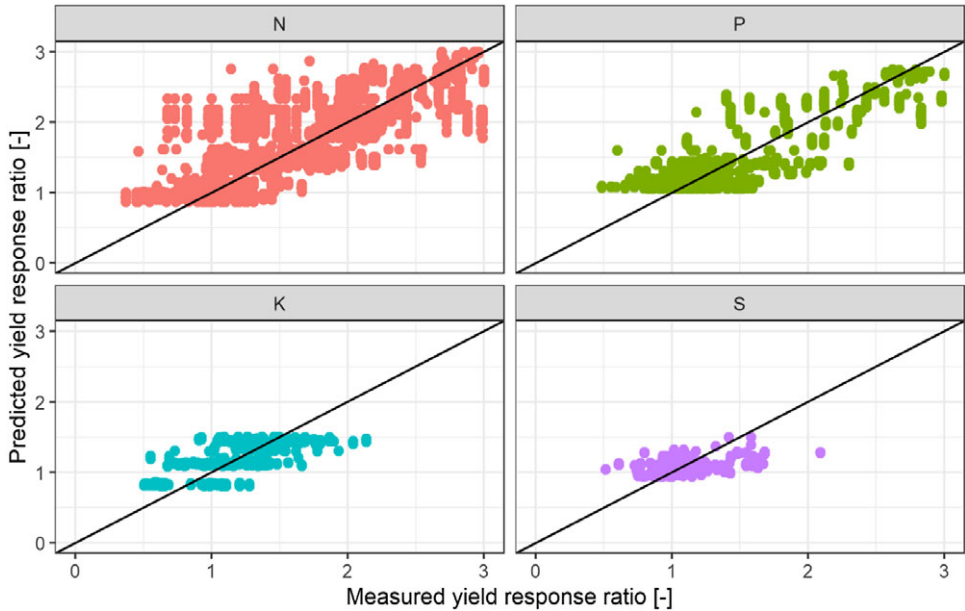
Figure 2. Scatter plot of model-predicted and measured yield using the model evaluation dataset of N, P, K, and S omission trials.
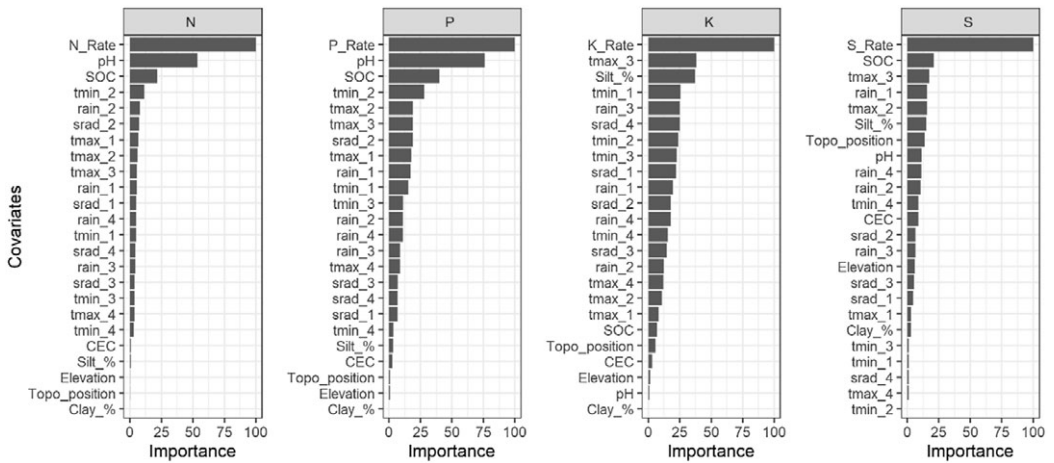

Figure 3. Random forest variable importance measures for N, P, K, and S responses.

high yield (or even decreasing), and similar evidence was reported in Amede *et al.* (2020). Yield response ratio decreases with increasing K could be due to its effect on the plant N metabolism; impact on the optimal N/P/K ratio needed for optimal yield response (Xu *et al.*, 2020); and inhibit Mg uptake and may induce Mg deficiency in plants (Tränkner *et al.*, 2018).

    We used the developed crop to nutrient response curves to identify the biophysical optimal nutrient. We presented the optimal level for N, P, and S for Basona Worena woreda for the year 2018 to show how the approach can develop site-specific fertilizer recommendation (Figure A1). The recommendation is just for the specific year and is not static as it varies with weather elements such as rainfall and temperature. The spatial variability of recommended optimal nutrients is high
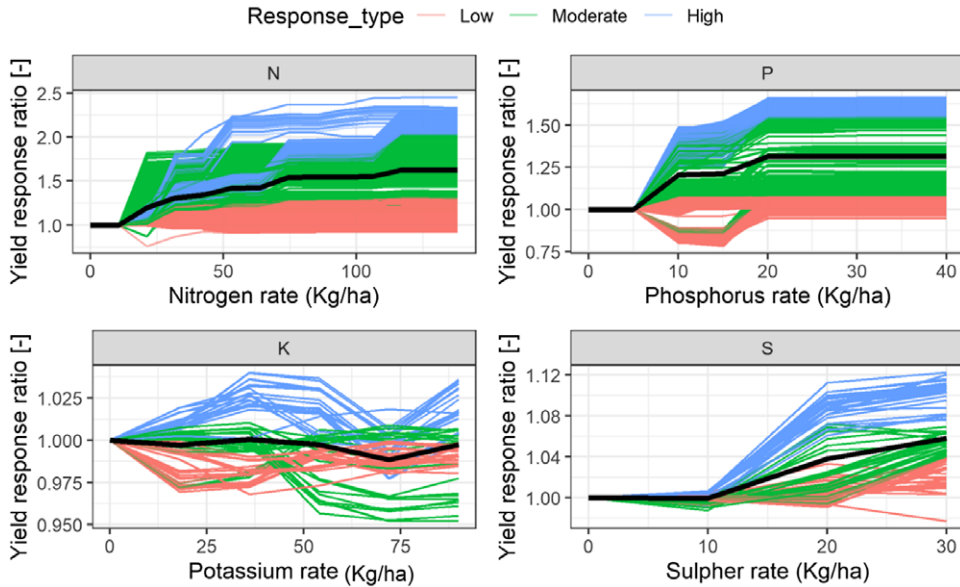
Figure 4. Wheat nutrient response curves for four nutrients (N, P, K, and S) at sites used for model evaluation. Individual sites and years are shown in colored lines; the thick black line shows the overall average response.

(Figure A1), indicating that the approach can be a useful to develop a tool to guide fertilizer decisions at any spatial and administrative scale which can range from lowest administrative unit like Kebele or Woreda to higher units like regional and federal level. For instance, at the Basona Worena woreda for the year 2018, our analysis shows that application of site-specific optimal N can increase on average about 263 kg/ha in comparison to the Blanket recommendation (i.e. 100 kg/ha) throughout the woreda (Figure A2).

Determinants of crop response to nutrients

The PC analysis shows that about 50% of the difference between the low, medium, and high response categories can be explained by the first and second PCs (Figure 5). For N, the first three components contributed about 62.1% of the total variation of the three nutrient response groups. Principal component one (PC1) alone explained 30% of the total variation for the N response groups. In PC1 climatic parameters (particularly solar radiation and temperature) and soil parameters (pH and elevation) had a strong loading in categorising the N response functions. On the other hand, elevation, rain_1, and SOC negatively correlated with PC1, indicating that they are not in the first order of variables determining N responses curves. In PC2, the first-month maximum temperature and elevation had a strong positive influence on N response groups (Figure 5a). Silt percentage and CEC are the key elements constituting PC3.

For P response groups, PC1, PC2, and PC3 explained 29%, 18%, and 16% of the variation, respectively. Radiation and temperature in PC1, texture and elevation in PC2, and temperature and topographic position in PC3 explained most of the variation in grouping P responses functions into the three categories (Figure 5b). PC1 correlates negatively with rainfall (Rain_1, Rain_2, Rain_3) in determining P response curve shapes.

With respect to K, PC1 explained more than 52% of the determinants for K response function groupings, with PC2 and PC3 having almost the same effects (11–12%) (Figure 5c). Most environmental covariates have contributions to PC1, whereas temperature covariates have a strong negative correlation with PC2, and rainfall has positive loading for PC3. The PCA for S response
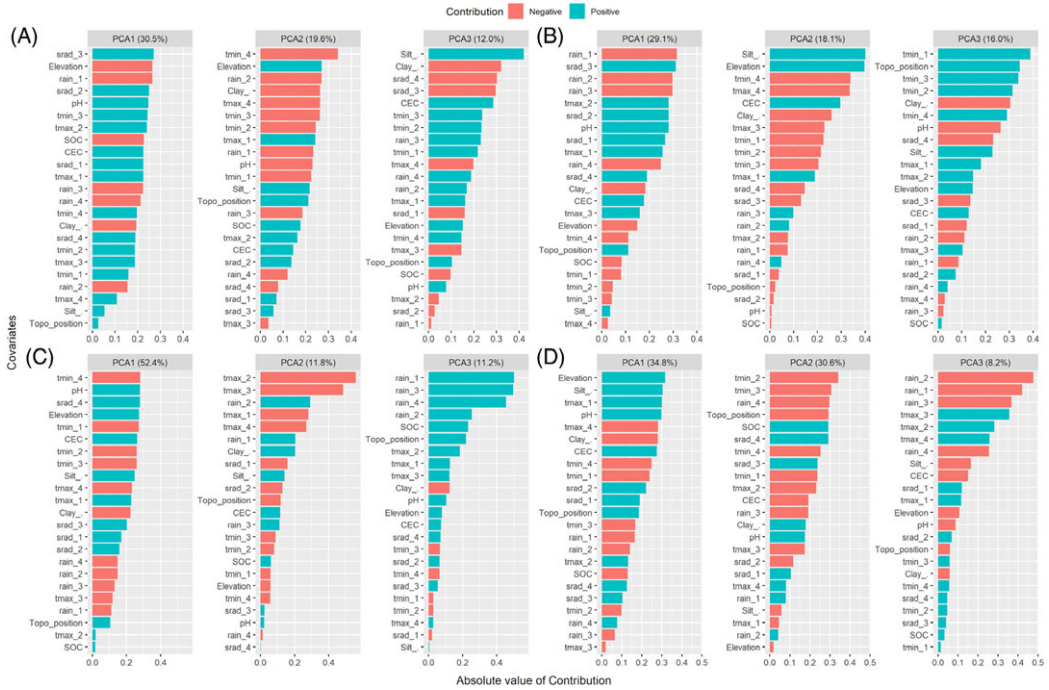
Figure 5. Principal component analysis for the three categories of response curves for four nutrients (N, P, K, and S) based on nutrient omission trials for (A) nitrogen, (B) phosphorous, (C) potassium, and (D) sulfur.

function showed that PC1 and PC2 had almost the same effect (30–34%) in explaining the S response function groupings, whereas PC3 explained only 8% of the variation (Figure 5c). PC1 has high and positive loadings on elevation, soil texture, pH, and temperature; PC2 has high loading with temperature and SOC. The former correlates negatively, the latter correlates positively (Figure 5c). PC3 correlates negatively with rainfall and positively with maximum temperature.

In all nutrient responses, many covariates contribute to the first PC. There are no single or two covariates with exceptional large loading, indicating that no single variables are determining the shape of the fertilizer response curve.

Discussion

Crop yields in Ethiopia need to increase considerably to reduce import dependency and keep up with the expected population increase and dietary changes. Despite the yield increase observed for many crops including wheat in recent years, crop yield gaps remain large. Although Ethiopia is the largest wheat producer in SSA, the country imported 1.5 million tonnes of wheat, corresponding to a value of around $600 million (CSA, 2019). Currently, the national average yield of wheat is 2.9 t/ha, or roughly 20% of the crop's rainfed yield potential (Silva *et al.*, 2021). Low and blanket fertilizer application has long been considered as the main cause of low yields in Ethiopia (Tamene *et al.*, 2017). Given the rapidly increasing demand for cereals due to fast population growth and dietary change in the country (van Ittersum *et al.*, 2016), the application of higher amounts of nutrients with higher agronomic and economic efficiency are needed to increase wheat productivity under rainfed systems.

In the present study, we aimed to develop site-specific nutrient response functions for wheat using large datasets collated from various *in situ* observations. The datasets were used to train and evaluate a ML model to develop wheat nutrient response functions for four nutrients (N, P, K, and S) at a fine spatial resolution. As shown by the statistical indices used to evaluate model performance against measured observations (Table 2), the developed model performed well in representing measured nutrient responses across Ethiopia's diverse wheat-growing environments. The study also categorized wheat-growing environments into three groups based on patterns of non-sentient functions to facilitate manageable nutrient recommendations across relatively similar response environments. Moreover, the study identified the major factors that influence nutrient response for each response group. Since the nutrient response functions are developed by considering all relevant climatic and edaphic factors, the response functions can be used to match fertilizer application rates with soil fertility problems effectively in the wheat-growing environments. Although most smallholder farmers appreciate the benefit of fertilizers, they rarely apply them at recommended rates and at the appropriate time because of unreliable returns, high cost, lack of supportive policy to access, and limited knowledge about their efficient use (Tamene *et al.*, 2017). Therefore, the availability of high-resolution fertilizer recommendations, such as the one developed for wheat in this study, can increase nutrient efficiency, affordability, and economic returns to smallholder farmers. Moreover, government policies aimed at increasing wheat production in rainfed systems should focus on fostering the accessibility and affordability of inputs, particularly fertilizers (Silva *et al.*, 2021).

The approach followed in this study is one step closer to developing precision nutrient management based on optimal fertilizer recommendations. This would help to fill the gap that exists between coarse resolution farming system or agroecology-based fertilizer recommendations and more complex process-based model approaches which have site-specific data and intensive calibration requirements (Basso *et al.*, 2011). The RF ML model presented in this study provided high-resolution nutrient recommendations compared with other fertilizer recommendation efforts such as OFRA (Wortmann and Sones, 2017) and the soil test-based methods of EthioSIS (Tegbaru, 2015).

The ML approach is data-driven and based on capturing important factors that determine yield by considering the important biophysical factors that influence yield. The approach thus has a huge potential to develop spatially explicit fertilizer recommendations for several crops which will be improved with increased availability and accessibility of agronomic and other agricultural data. Note, however, that further improvement will be needed to minimize uncertainties associated with the ML approach as more data with several temporal and spatial dimensions become available. In future, the ML model can be improved by considering: (1) the use of organic fertilizers and new crop varieties for different crops; (2) high-resolution and updated soil datasets such as the data collected by the EthioSIS project; and (3) innovations around agronomic data acquisition technologies (e.g. 'internet of things') from crop plots which can facilitate real-time data streaming to help improve the predictive capacity of models.

Conclusion

This study used data from nutrient omission field trials conducted across the diverse wheat-growing environments in Ethiopia to develop site-specific nutrient response functions using a ML approach. The RF model developed for predicting wheat response to N, P, K, and S nutrients at the different sites performed well when it is compared against observed records, particularly for N, P, and S. The ML model also provided high-resolution nutrient recommendations compared with other previous fertilizer recommendation efforts in Ethiopia. Moreover, the ML approach enabled us to identify the major climatic and soil conditions that influence the response of wheat to the four nutrients studied. The study demonstrated the potential of using ML

approaches for developing spatially explicit nutrient response functions and fertilizer recommendations by using wheat as a case study crop. The study suggested the need for further improvement to minimize uncertainties associated with the current approach as more data with several temporal and spatial dimensions become available soon. The approach will help develop decision support tools for site-specific nutrient recommendations by smallholder farmers and thereby enhance nutrient use efficiency and increase yield and income. This research is expected to respond to the national policy demands for a sound method to identify the optimal fertilizer rate to increase economic returns for fertilizer investments and take fertilizer utilization research one step further. It is useful to set an evidence-based threshold (limit) of nutrients, above which additional applications are prohibited or limited due to a low probability of positive crop response and a high probability of negative environmental impacts on soil and water.

References

Abatzoglou J.T., Dobrowski S.Z., Parks S.A. and Hegewisch K.C. (2018). TerraClimate, a high-resolution global dataset of monthly climate and climatic water balance from 1958–2015. *Scientific Data* **5**, 170191. doi: 10.1038/sdata.2017.191

Amede T., Gashaw T., Legesse G., Tamene L., Mekonen K., Thorne P. and Schultz S. (2020). Landscape positions dictating crop fertilizer responses in wheat-based farming systems of East African Highlands. *Renewable Agriculture and Food Systems*, 1–13. doi: 10.1017/S1742170519000504

Anteneh A. and Asrat D. (2020). Wheat production and marketing in Ethiopia: review study. *Cogent Food & Agriculture* **6**, 1–14. doi: 10.1080/23311932.2020.1778893

Basso B., Ritchie J.T., Cammarano D. and Sartori L. (2011). A strategic and tactical management approach to select optimal N fertilizer rates for wheat in a spatially variable field. *European Journal of Agronomy* **35**, 215–222. doi: 10.1016/j.eja.2011.06.004

Breiman L. (2001). Random forests. *Machine Learning* **45**, 5–32. doi: 10.1023/A: 1010933404324

Chianu J.N., Chianu J.N. and Mairura F. (2012). Mineral fertilizers in the farming systems of sub-Saharan Africa. A review. *Agronomy for Sustainable Development* **32**, 545–566. doi: 10.1007/s13593-011-0050-0

Chlingaryan A., Sukkarieh S. and Whelan B. (2018). Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: a review. *Computers and Electronics in Agriculture* **151**, 61–69.

CSA. (2019). *Agriculture Sample Survey 2018/2019: Volume I Report on Area and Production of Major Crops.* Addis Ababa: 589 Statistical Bulletin.

CSA (Central Statistical Agency). (2016). *Area and Production of Crops in the Meher Season.* Addis Ababa: Statistical Bulletin, Central Statistical Agency (CSA).

Cutler D.R., Edwards T.C. Jr., Beard K.H., Cutler A., Hess K.T., Gibson J. and Lawler J.J. (2007). Random forests for classification in ecology. *Ecology* **88**, 2783–2792. doi: 10.1890/07-0539.1

Delerce S., Dorado H., Grillon A., Rebolledo M.C., Prager S.D., Patiño V.H., Varón G.G. and Jiménez D. (2016). Assessing weather-yield relationships in rice at local scale using data mining approaches. *PLoS ONE* **11**, e0161620. doi: 10.1371/journal.pone.0161620

EIAR (Ethiopian Institute of Agricultural Research). (2020) Optimizing Fertilizer Recommendations for Africa (OFRA) Database. Available at http://ec2-54-93-187-2'55.eu-central-1.compute.amazonaws.com/organization/eiar (accessed 5 August 2021).

Fei L., Meijun Z., Jiaqi S., Zehui C., Xiaoli W. and Jiuchun Y. (2020). Maize, wheat and rice production potential changes in China under the background of climate change. *Agricultural Systems* **182**, 102853. doi: 10.1016/j.agsy.2020.102853

Fick S.E. and Hijmans R.J. (2017). WorldClim 2: new 1-km spatial resolution climate surfaces for global land areas. *International Journal of Climatology* **37**, 4302–4315. doi: 10.1002/joc.5086

Friedman J., Hastie T. and Tibshirani R. (2001). *The Elements of Statistical Learning*. New York: Springer Series in Statistics.

Garnett T., Appleby M.C., Balmford A., Bateman I.J., Benton T.G., Bloomer P., Burlingame B., Dawkins M., Dolan L., Fraser D., Herrero M., Hoffmann I., Smith P., Thornton P.K., Toulmin C., Vermeulen S.J. and Godfray H.C.J. (2013). Sustainable intensification in agriculture: premises and policies. *Science* **341**, 33–34. doi: 10.1126/science.1234485

Getnet Z., Husen A., Fetene M. and Yemata G. (2015). Growth, water status, physiological, biochemical and yield response of stay green sorghum (*Sorghum bicolor* (L.) Moench) varieties-a field trial under drought-prone area in Amhara Regional State, Ethiopia. *Journal of Agronomy* **14**, 188–202. doi: 10.3923/ja.2015.188.202

Goldstein A., Kapelner A., Bleich J. and Pitkin E. (2015). Peeking inside the black box: visualizing statistical learning with plots of individual conditional expectation. *Journal of Computational and Graphical Statistics* **24**, 44–65. doi: 10.1080/10618600.2014.907095

Hengl T., Mendes de Jesus J., Heuvelink G.B., Ruiperez Gonzalez M., Kilibarda M., Blagotić A., Shangguan W., Wright M.N., Geng X., Bauer-Marschallinger B. and Guevara M.A. (2017). SoilGrids250m: global gridded soil information based on machine learning. *PLoS ONE* **12**, e0169748. doi: 10.1371/journal.pone.0169748

Hodson D.P., Jaleta M., Tesfaye K., Yirga C., Beyene H., Kilian A., Carling J., Disasa T., Alemu S.K., Daba T. and Alemayehu Y. (2020). Ethiopia's transforming wheat landscape: tracking variety use through DNA fingerprinting. *Scientific Reports* **10**, 1–13. doi: 10.1038/s41598-020-75181-8

Hoffman A.L., Kemanian A.R. and Forest C.E. (2018). Analysis of climate signals in the crop yield record of Sub-Saharan Africa. *Global Change Biology* **24**, 143–157. doi: 10.1111/gcb.13901

Jarvis A., Guevara E., Reuter H.I. and Nelson A.D. (2008). Hole-filled SRTM for the globe. Version 4: data grid. Available at http://srtm.csi.cgiar.org (accessed 5 August 2021).

Jeong J.H., Resop J.P., Mueller N.D., Fleisher D.H., Yun K., Butler E.E., Timlin D.J., Shim K.M., Gerber J.S., Reddy V.R. and Kim S.H. (2016). Random forests for global and regional crop yield predictions. *PLoS ONE* **11**, e0156571.

Jiménez D., Delerce S., Dorado H., Cock J., Muñoz L.A., Agamez A. and Jarvis A. (2019). A scalable scheme to implement data-driven agriculture for small-scale farmers. *Global Food Security* **23**, 256–266. doi: 10.1016/j.gfs.2019.08.004

Kaizzi K.C., Mohammed M.B. and Nouri M. (2017). Fertilizer use optimization: principles and approach. In Wortmann C.S. and Sones K. (eds), *Fertilizer Use Optimization in Sub-Saharan Africa*. Nairobi: CABI, pp. 9–19.

Kalra N., Chakraborty D., Kumar P.R., Jolly M. and Sharma P.K. (2007). An approach to bridging yield gaps, combining response to water and other resource inputs for wheat in northern India, using research trials and farmers' fields data. *Agricultural Water Management* **93**, 54–64. doi: 10.1016/j.agwat.2007.06.004

Kassie M., Zikhali P., Manjur K. and Edwards S. (2009). Adoption of sustainable agriculture practices: evidence from a semi-arid region of Ethiopia. *Natural Resource Forum* **33**, 189–198. doi: 10.1111/j.1477-8947.2009.01224.x

Khush G.S. (2001). Green revolution: the way forward. *Nature Reviews Genetics* **2**, 815–822. doi: 10.1038/35093585

Kihara J., Bolo P., Kinyua M., Nyawira S.S., & Sommer R. (2020). Soil health and ecosystem services: lessons from sub-Sahara Africa (SSA). *Geoderma* **370**, 114342. doi: 10.1016/j.geoderma.2020.114342

Kihara J. and Njoroge S. (2013). Phosphorus agronomic efficiency in maize-based cropping systems: a focus on western Kenya. *Field Crops Research* **150**, 1–8. doi: 10.1016/j.fcr.2013.05.025

Kihara J., Tibebe D., Gurmessa B. and Desta L. (2017). *Towards Understanding Fertilizer Responses in Ethiopia. Harvard Dataverse, V2*. Addis Ababa: International Center for Tropical Agriculture (CIAT).

Kihara J., Nziguheba G., Zingore S., Coulibaly A., Esilaba A., Kabambe V., Njoroge S., Palm C. and Huising J. (2016). Understanding variability in crop response to fertilizer and amendments in sub-Saharan Africa. *Agriculture, Ecosystems & Environment* **229**, 1–12. doi: 10.1016/j.agee.2016.05.012

Koning N. and van Ittersum M.K. (2009). Will the world have enough to eat? *Current Opinion in Environmental Sustainability* **1**, 77–82. doi: 10.1016/j.cosust.2009.07.005

Kuhn M. (2008). Building predictive models in R using the caret package. *Journal of Statistical Software* **28**, 1–26. http://www.jstatsoft.org

Kuhn M. and Johnson K. (2013). *Applied Predictive Modeling*. New York: Springer.

Li T., Hasegawa T., Yin X., Zhu Y., Boote K., Adam M., Bregaglio S., Buis S., Confalonieri R., Fumoto T. and Gaydon D. (2015). Uncertainties in predicting rice yield by current crop models under a wide range of climatic conditions. *Global Change Biology* **21**, 1328–1341. doi: 10.1111/gcb.12758

Marenya P.P., Gebremariam G., Jaleta M. and Rahut D.B. (2020). Sustainable intensification among smallholder maize farmers in Ethiopia: adoption and impacts under rainfall and unobserved heterogeneity. *Food Policy* **95**, 101941. doi: 10.1016/j.foodpol.2020.101941

Minot N., Warner J., Lemma S., Abate G. and Rashid S. (2019). *The Wheat Supply Chain in Ethiopia: Patterns, Trends, and Policy Options*. Washington, DC: IFPRI.

Moswetsi G., Fanadzo M. and Ncube B. (2017). Cropping systems and agronomic management practices in smallholder farms in South Africa: constraints, challenges and opportunities. *Journal of Agronomy* **16**, 51–64. doi: 10.3923/ja.2017.51.64

Otsuka K. and Larson D. F. (eds.) (2012). *An African Green Revolution: Finding Ways to Boost Productivity on Small Farms.* Switzerland AG: Springer Science & Business Media.

Rodriguez D.G.P. (2020). An assessment of the site-specific nutrient management (SSNM) strategy for irrigated rice in Asia. *Agriculture* **10**, 559. doi: 10.3390/agriculture10110559

Searchinger T., Waite R., Hanson C., Ranganathan J., Dumas P., Matthews E. and Klirs C. (2019). *Creating a Sustainable Food Future: A Menu of Solutions to Feed Nearly 10 Billion People by 2050.* Washington, DC: WRI.

Shahhosseini M., Martinez-Feria R.A., Hu G. and Archontoulis S.V. (2019). Maize yield and nitrate loss prediction with machine learning algorithms. *Environmental Research Letters* **14**, 124026.

Silva J.V., Baudron F., Reidsma P. and Giller K.E. (2019). Is labor a major determinant of yield gaps in sub-Saharan Africa? A study of cereal-based production systems in Southern Ethiopia. *Agricultural Systems* **174**, 39–51. doi: 10.1016/j.agsy.2019.04.009

Silva J.V., Reidsma P., Baudron F., Jaleta M., Tesfaye K. and van Ittersum M.K. (2021). Wheat yield gaps across small-holder farming systems in Ethiopia. *Agronomy for Sustainable Development* **41**, 1–16. doi: 10.1007/s13593-020-00654-z

Spielman D.J., Byerlee D., Alemu D. and Kelemework D. (2010). Policies to promote cereal intensification in Ethiopia: the search for appropriate public and private roles. *Food Policy* **35**, 185–194. doi: 10.1016/j.foodpol.2009.12.002

Stewart Z.P., Pierzynski G.M., Middendorf B.J. and Prasad P.V. (2020). Approaches to improve soil fertility in sub-Saharan Africa. *Journal of Experimental Botany* **71**, 632–641. doi: 10.1093/jxb/erz446

Svetnik V., Liaw A., Tong C., Culberson J.C., Sheridan R.P. and Feuston B.P. (2003). Random forest: a classification and regression tool for compound classification and QSAR modeling. *Journal of Chemical Information and Computer Sciences* **43**, 1947–1958. doi: 10.1021/ci034160g

Tamene L., Amede T., Kihara J., Tibebe D. and Schulz S. (2017). A review of soil fertility management and crop response to fertilizer application in Ethiopia: towards development of site-and context-specific fertilizer recommendation. CIAT Publication no. 443. Available at www.cgiar.org (accessed 5 August 2021).

Tegbaru, B. (2015). Soil Fertility Mapping and Fertilizer Recommendation in Ethiopia: Update of EthioSIS project and status of fertilizer blending plants. 2nd IPI–MoANR–ATA-Hawassa University Joint Symposium. The role of potassium in balanced fertilization, 24–26.

Thelemann R., Johnson G., Sheaffer C., Banerjee S., Cai H. and Wyse D. (2010). The effect of landscape position on biomass crop yield. *Agronomy Journal* **102**, 513–522. doi: 10.2134/agronj2009.0058

Tittonell P. and Giller K.E. (2013). When yield gaps are poverty traps: the paradigm of ecological intensification in African smallholder agriculture. *Field Crops Research* **143**, 76–90. doi: 10.1016/j.fcr.2012.10.007

Tittonell P., Zingore S., Van Wijk M.T., Corbeels M. and Giller K.E. (2007). Nutrient use efficiencies and crop responses to N, P and manure applications in Zimbabwean soils: exploring management strategies across soil fertility gradients. *Field Crops Research* **100**, 348–368. doi: 10.1016/j.fcr.2006.09.003

Tränkner M., Tavakol E. and Jákli B. (2018). Functioning of potassium and magnesium in photosynthesis, photosynthate translocation and photoprotection. *Physiologia Plantarum* **163**, 414–431.

Van Ittersum M.K., Van Bussel L.G., Wolf J., Grassini P., Van Wart J., Guilpart N., Claessens L., De Groot H., Wiebe K., Mason-D'Croz D. and Yang H. (2016). Can sub-Saharan Africa feed itself? *Proceedings of the National Academy of Sciences* **113**, 14964–14969. doi: 10.1073/pnas.1610359113

Vanlauwe B., Coyne D., Gockowski J., Hauser S., Huising J., Masso C., Nziguheba G., Schut M. and van Asten P. (2014). Sustainable intensification and the African smallholder farmer. *Current Opinion in Environmental Sustainability* **8**, 15–22. doi: 10.1016/j.cosust.2014.06.001

Vanlauwe B., Kihara J., Chivenge P., Pypers P., Coe R. and Six J. (2011). Agronomic use efficiency of N fertilizer in maize-based systems in sub-Saharan Africa within the context of integrated soil fertility management. *Plant and Soil* **339**, 35–50. doi: 10.1007/s11104-010-0462-7

Wanzala M. and Groot R. (2013). Fertiliser market development in Sub-Saharan Africa. In Proceedings-International Fertiliser Society (No. 731). International Fertiliser Society. Available at http://www.fertiliser-society.org/ (accessed 5 August 2021).

Willmott C.J., Ackleson S.G., Davis R.E., Feddema J.J., Klink K.M., Legates D.R., O'donnell J. and Rowe C.M. (1985). Statistics for the evaluation and comparison of models. *Journal of Geophysical Research: Oceans* **90**, 8995–9005.

Wortmann C.S. and Sones K. (2017). *Fertilizer Use Optimization in Sub-Saharan Africa.* Nairobi: CABI.

Xu X., Du X., Wang F., Sha J., Chen Q., Tian G., Zhu Z., Ge S. and Jiang, Y. (2020). Effects of potassium levels on plant growth, accumulation and distribution of carbon, and nitrate metabolism in apple dwarf rootstock seedlings. *Frontiers in Plant Science* **11**, 904.

Zegeye T. (2001). Agricultural Research System of Ethiopia: past History and Future Vision. International Conference on African Development Archives. 38. ScholarWorks at Western Michigan University. Available at https://scholarworks.wmich.edu/africancenter_icad_archive/38 (accessed 5 August 2021).
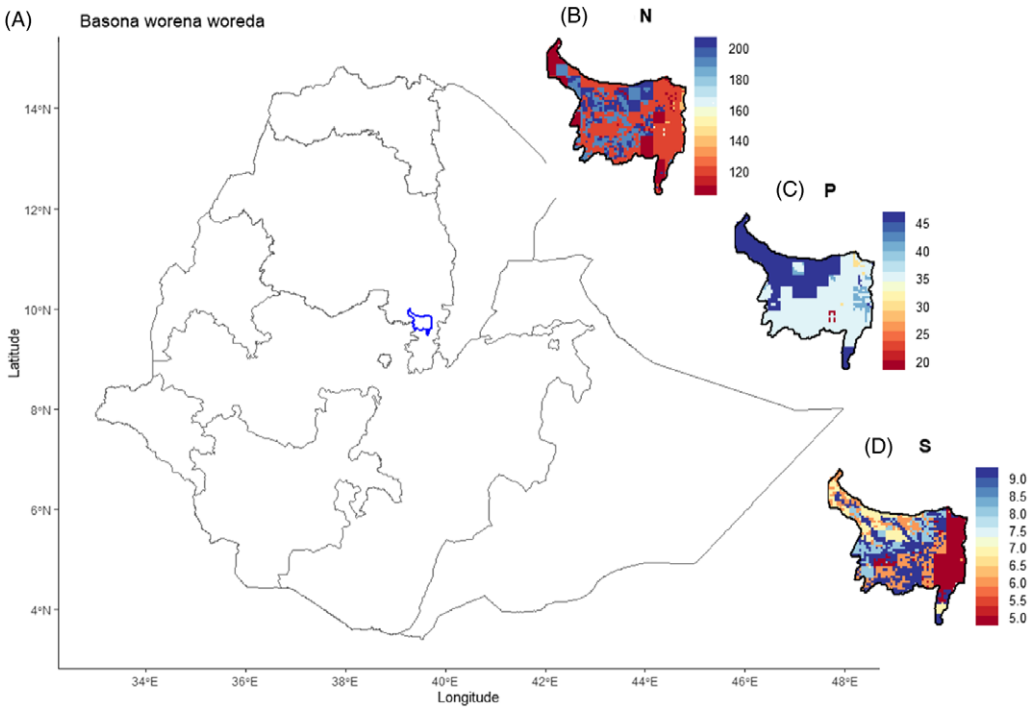
Appendix

Figure A1. Spatial optimal nutrient recommendation rate based on RF model for Basona Worena woreda as an example. A) location map of Baona worena woreda overlayed on map of Ethiopia, B) the optimal nutrient rate for N, C) optimal nutrient rate for P, C) optimal nutrient rate for S. Please note that optimla rate for K is not mapped here.
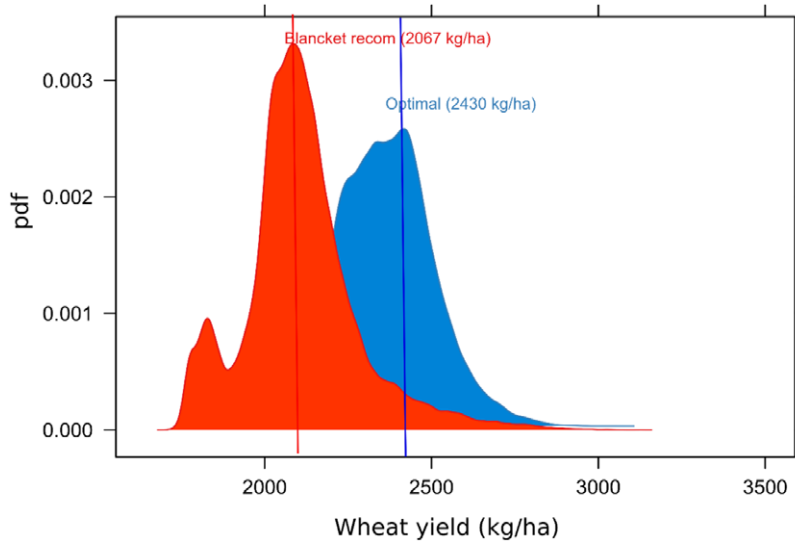
Figure A2. The probability distribution of wheat yield for blanket (100 kg/ha) and biophysical optimal N applications in Basona worena woreda.