



# Novel insights into factors associated with yield response and nutrient use efficiency of maize and rice in sub-Saharan Africa. A review

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## Abstract

A common theme emerging from nutrient omission trials conducted extensively across sub-Saharan Africa has been the large variability in yield response to applied nutrients. Yet, little is known about the factors associated with this variability. Therefore, the objectives of this review were to (1) synthesize the available data from nutrient omission trials of maize and rice and quantify spatial variability in yield responses and the probability of attaining specified yield targets; (2) identify the genotypic, environmental, and nutrient management factors associated with yield responses; and (3) provide insights and actionable information for setting priorities for future nutrient management research and development. Here, we provide distributions and expected values of yield response and agronomic efficiencies of nitrogen (N), phosphorus (P), and potassium (K) to serve as benchmarks for improving fertilizer recommendations. We also show that with the combined application of NPK fertilizer, rain-fed maize and rice yields can be raised from the current yields of  $\sim 2 \text{ Mg ha}^{-1}$  to  $4 \text{ Mg ha}^{-1}$ . Yield responses to N, P, and K were in the ratio of 11:6:1 in maize and 13:7:5 in rice, probably arising from differences in uptake requirements and growing environments. K yield responses were 2–3 times higher in rice than in maize. Explorative analysis using machine learning algorithms provided further insights into the possible interaction of agroecology, soil type, and exchangeable cations on the spatial variability in yield responses to N, P, and K in maize and rice. We recommend future research to address site-specific interactions between the applied and indigenous soil nutrients, focusing on optimizing application rates of K, other macronutrients and micronutrients for sustainable intensification of maize and rice production. This study highlights the critical need for balanced fertilization to optimize the productivity and nutrient use efficiencies in rice and maize production in smallholder farming systems in SSA.

**Keywords** Machine learning algorithms · Nutrient interactions · Sustainable intensification

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## 1 Introduction

Despite the availability of improved cultivars and agronomic management options, the productivity of staple cereals such as maize and rice has remained low in many countries in sub-Saharan Africa (SSA) (Grassini et al. 2013; Kuyah et al. 2021). In some countries, up to 200 improved maize varieties and 570 improved rice varieties with yield potentials exceeding 5 Mg ha<sup>-1</sup> have been released since the 1960s (Abate et al. 2017; Futakuchi et al. 2021; Kuyah et al. 2021), yet yields on farmers' fields are far below the yield potentials (van Dijk et al. 2017), with current mean maize and rice yields estimated at 1.6 and 2.1 Mg ha<sup>-1</sup>, respectively (USDA 2020). Past production gains in SSA were achieved mainly by increasing the area under production, a trend that is not sustainable in the future (Arouna et al. 2021; Cairns et al. 2021; Kuyah et al. 2021). To meet the food needs of future generations, maize production must increase from the current ~20% of water-limited yield potential (WYP) to 50–75% of WYP (Ten Berge et al. 2019). The WYP of maize ranges from 6 to 13.9 Mg ha<sup>-1</sup> across nine major maize-producing countries in SSA (GYGA 2021). Similarly, the WYP of rice is in the range of 4.1–8.5 Mg ha<sup>-1</sup> in irrigated lowland systems (GYGA 2021). Agronomic practices that support sustainable intensification, including nutrient management, constitute the most critical factors for reducing the yield gaps (Kuyah et al. 2021; Saito et al. 2021; Vandamme et al. 2018).

From an agronomic perspective, poor soil fertility is the primary factor limiting agricultural productivity in SSA (Giller 2021; Saito et al. 2019). While increased fertilizer use is necessary to improve cereal crop yields in nutrient-depleted soils in SSA, frequent occurrences of low and variable crop yields following increased fertilizer applications limit the use of fertilizers by smallholder farmers (Cairns et al. 2021; Chamberlin et al. 2021). For example, the

application of the recommended N, P, and K fertilizers failed to increase maize yields by more than 0.5 Mg ha<sup>-1</sup> in up to 68% of farmers' fields in Kenya, DR Congo, Tanzania, and Nigeria (Roobroeck et al. 2021). Crop yield response to applied fertilizer is often limited by low soil organic matter (SOM), moisture stress, soil acidity, and associated toxicities prevalent in maize and rice production systems across SSA (Agegnehu et al. 2021; Chamberlin et al. 2021; Tsujimoto et al. 2019). Unbalanced nutrient applications and suboptimal agronomic practices have also been identified as key factors limiting crop yield responses to increased fertilizer applications (Bindraban et al. 2015; Kihara et al. 2016; Mtangadura et al. 2017; Roobroeck et al. 2021; Ten Berge et al. 2019; van der Velde et al. 2014; Fig. 1). Recent analyses (e.g., Aliyu et al. 2021; Kihara et al. 2017; Mtangadura et al. 2017; Tsujimoto et al. 2019) have documented diminished responses to NPK fertilizers due to widespread deficiencies of other macronutrients and micronutrients. For example, in a long-term experiment in Zimbabwe, the decline in maize yields was linked to depletion of soil exchangeable Ca, Mg, and K and concomitant reduction in soil pH under continuous application of low rates of N fertilizer (Mtangadura et al. 2017). Accelerated loss of Ca, Mg, and K with mineral N fertilization was attributed to their removal with crop off-take and leaching of NO<sub>3</sub><sup>-</sup>, which is accompanied by exchangeable cations to maintain electrical balance (Mtangadura et al. 2017).

While crop yield responses to nutrient applications are highly heterogeneous under various climatic, soil, and water management conditions (Ibrahim et al. 2021; Waqas et al. 2020), fertilizer recommendations in many countries in SSA are mostly generalized and are rarely tailored to site-specific growing conditions. Most of these recommendations apply to large administrative areas or agroecological zones (Rurinda et al. 2020; Snapp et al. 2003), despite the variability of environmental and farmer management factors at short distances in the smallholder landscapes (Zingore et al. 2007).

To enhance crop productivity and reduce the variability in crop yield responses to fertilizer application, there is growing emphasis on the need for site-specific nutrient management (SSNM) practices (Buresh et al. 2019; Chivenge et al. 2021; Dobermann et al. 2002; Saito et al. 2015, 2019). The SSNM concept (Dobermann et al. 2002) uses nutrient omission trials (NOTs) as a basis for generating data for estimating crop nutrient requirements for specific crops, and soil and climatic conditions (Buresh et al. 2019; Chivenge et al. 2021). NOTs provide information about the indigenous soil nutrient supply capacity and crop response to nutrient application from which site-specific nutrient recommendations are estimated for a targeted yield (Buresh et al. 2019; Dobermann et al. 2002). Over the last decades, a large number of NOTs have been implemented across SSA, focusing mainly on maize and rice (Kihara et al. 2015; Njoroge et al. 2017; Nziguheba et al.

**Fig. 1** An aerial view of maize nutrient omission plots in northern Ghana. Treatments are Control, no nutrient input; PK, N omission; NK, P omission; NP, K omission; NPK, no omission; NPK+SMN = NPK +other macronutrients and micronutrients added.



2009; Rurinda et al. 2020; Saito et al. 2019; Shehu et al. 2018; Vanlauwe et al. 2006). Several researchers have analyzed the data generated (e.g., Aliyu et al. 2021; Kafesu et al. 2018; Kenea et al. 2021; Kihara et al. 2015; Kihara et al. 2016; Kurwakumire et al. 2014; Njoroge et al. 2017; Nziguheba et al. 2009; Rurinda et al. 2020; Saito et al. 2019; Shehu et al. 2018; Vanlauwe et al. 2006), but inferences have mainly focused on mean responses in isolated studies. Inferences based on means can, however, lead to ecological fallacy, which occurs when the response of individuals is deduced from inferences about the group, for example, when a statement such as “the mean response of maize to K application is not significantly different from zero” (Ten Berge et al. 2019) is interpreted as “K is non-limiting in African soils,” as is the case in many fertilizer recommendations omitting K (*cf.* chapters in Wortmann and Sones 2016). Another common theme emerging from these analyses has been the large variability in the trends of yield response to applied nutrients, which affects fertilizer use efficiency and crop productivity (Kihara et al. 2016; Niang et al. 2017; Njoroge et al. 2017; Rurinda et al. 2020; Saito et al. 2019). However, our knowledge of the factors that drive the variability in nutrient responses at scale is still limited. Information on the possible values of attainable yields, yield responses to individual nutrients, and agronomic efficiencies is not well integrated to judge the sustainability of maize and rice production systems. The distributions of attainable yields; use efficiencies of N, P, and K; and associated conditions have not been adequately addressed in the literature reviewed. Therefore, there are major

gaps in the integrated analysis of available key data to assess crop yield response patterns, and the conditions that dictate response patterns. Such analysis is essential for providing insights into how fertilizer can be used effectively to sustainably increase crop yields while decreasing the variability in yield responses and optimizing nutrient use efficiency.

This review aimed to identify critical factors associated with yield responses and draw parallels in genotypic, environmental, and management factors that influence nutrient responses in maize and rice using linear mixed modeling and supplementary analysis with machine learning algorithms. The objectives of this paper are to (1) synthesize the available regional data from nutrient omission trials of maize and rice and quantify spatial variability in yield responses and the probability of attaining benchmark yield targets; (2) identify the genotypic, environmental, and nutrient management factors associated with yield responses; and (3) provide insights and actionable information for setting priorities for future investments in nutrient management research and development.

## 2 Review and data analysis

### 2.1 Context of the review

We chose maize and rice as the crops of focus because of the large volumes of nutrient omission trial data available and their strategic importance for food security in SSA (Abate et al. 2017; Arouna et al. 2021; Ibrahim et al. 2021; Sileshi

and Gebeyehu 2021; Tsujimoto et al. 2019). Maize and rice rank first and second in terms of total cereal production in Africa (FAOSTAT 2019), yet many African countries have deficits and depend on substantial imports to supplement local production (Sileshi and Gebeyehu 2021).

In much of SSA, maize is grown under rainfed conditions, where water, nutrients, soil, and other agronomic constraints impose major yield limitations (van Ittersum et al. 2013). For rice, irrigated lowland (IL), rainfed lowland (RL), and rainfed upland (RU) production systems represent contrasting environments and constraints (Niang et al. 2017). Under irrigated conditions with a non-limiting water supply, the attainable rice yields are mainly determined by varieties, nutrient inputs, and agronomic management (van Ittersum et al. 2013). Under rainfed conditions, attainable yields are additionally affected by precipitation (van Ittersum et al. 2013), soil texture, bulk density, and rooting depth (Cambouris et al. 2016; Nyakudya and Stroosnijder 2014).

## 2.2 Literature search and data acquisition

We adopted a structured process to conduct the literature search for the review and included papers based on predefined selection criteria. The general format for searches was based on the Population Intervention Comparator Outcome categories complemented by the authors' expert knowledge of the subject area. The inclusion/exclusion criteria for papers or datasets to be considered for the analysis were as follows: (1) randomized and replicated on-farm nutrient omission trials of maize and rice from any area of SSA; (2) replication can be within or across sites; (3) must satisfy the minimum data requirement, namely, identifiable site name, study type (e.g., on research station or farmers' fields), year/season of implementation, variety, yields and yield components and pre-planting soil analysis; (4) trials that provide a minimum set of four treatments, namely NPK (no macronutrient omitted), PK (N omitted), NK (P omitted), NP (K omitted) to determine response to N, P and K responses; and (5) published or unpublished datasets. Our search strategy and details of the search including the keywords are summarized in the Supplementary Methods.

From the studies selected, we compiled primary data on nutrient application rates, crop genotypes, grain yield (i.e., dry weight in  $t\ ha^{-1}$ ), soil texture, soil organic carbon (SOC), soil pH, total N, available P, exchangeable K, Ca and Mg recorded at the commencement of each trial. In the maize dataset, primary data came from studies conducted for a duration ranging from 1 to 7 seasons on farmers' fields across 35 sites in seven countries. In the case of rice, the primary data came from trials conducted for 1–2 seasons on 1,037 farmers' fields across 30 sites in 17 countries, of which 12 sites were in irrigated lowland, 15 in rainfed lowland, and 3 in rainfed upland systems (Saito et al. 2019).

In all trials, relatively high N, P, and K rates were applied to achieve high yield targets. The minimum and maximum N, P, and K application rates in maize NOTs were 100 and 150, 22 and 50, and 30 and 60  $kg\ ha^{-1}$ , respectively. In all but one of the maize studies, nutrients were supplied through spot application close to the planting hole or planting hill during basal and top-dress applications. The one study where this was not the case included the application of 100  $kg\ N\ ha^{-1}$ , 100  $kg\ P\ ha^{-1}$ , and 100  $kg\ K\ ha^{-1}$ , with a third of the N fertilizer and the entire amounts of P and K fertilizer applied through broadcasting and incorporation in the whole experimental plot before planting, and the rest of the N fertilizer applied through banding of urea in the maize rows as topdressing (Vanlauwe et al. 2006). The minimum and maximum N, P, and K application rates in irrigated lowland rice were 160 and 200, 25 and 30, and 70 and 100  $kg\ ha^{-1}$ , respectively. In both rainfed lowland and upland rice, the minimum and maximum N, P, and K application rates were 110 and 160, 20 and 25, and 50 and 70  $kg\ ha^{-1}$ , respectively. All fertilizer applications in the rice trials were applied through broadcasting. At some sites, the maize trials also included the combined application of NPK and other macronutrients and micronutrients (hereafter referred to as NPK + SMN), combined application of NPK and lime (NPK + lime), and combined application of NPK and manure (NPK + manure). A total of 24 sites had NPK + Ca + Mg + S + Zn + B where Ca, Mg, S, and Zn were applied at 10, 5, 5, and 3  $kg\ ha^{-1}$ , respectively, with trace amounts of B. Manure was applied at 10  $Mg\ ha^{-1}$  on dry matter basis and lime at 500  $kg\ ha^{-1}$ . Analysis of management effects focused on nutrient inputs since all other crop management practices (e.g., weeding, planting date, density, etc.) had been applied uniformly following the recommended practices across all the trial sites.

The maize and rice genotypes differed in their improvement status (hybrid or open-pollinated), maturity dates (early, medium, or late maturity), and yield potential in the different trials. A total of 16 maize and 98 rice varieties were used in the NOTs. This meant that the same variety was not used across many sites. However, maturity dates were available for the different varieties. Therefore, we captured the genotype component by maturity groups.

Soil data were collected using different analytical methods or expressed in different units. For example, soil P was analyzed using Olsen or Mehlich extraction. Before combining such data for analysis, these were standardized and converted into a single unit using pedo-transfer functions. Available P given in Olsen P was converted into Mehlich III P as follows:  $0.68+2.33\ Olsen\ P$  for the sites with soil pH at 5.9 to 8.1, and  $0.133+1.987\ Olsen\ P$  for other sites (Buondonno et al. 1992; Mallarino and Blackmer 1992). We opted for simple conversion functions due to the limited soil parameters measured across all study sites. However, this may result in high uncertainty in the converted available P values. To standardize data

for combined analysis, available P was expressed in  $\text{mg kg}^{-1}$ , and exchangeable cations were expressed in  $\text{cmol kg}^{-1}$ , while SOC and total N were expressed in %. The soil C:N ratios and cations ratios, namely, Ca:K, Mg:K, and Ca:Mg, were derived on a meq basis (considering electrical charge) from exchangeable K, Ca, and Mg values. These ratios were calculated to indicate imbalances and availability of one element over the other on the cation exchange complex. In addition, the structural stability index (SSI) was calculated as an indicator of degradation and the sufficiency of soil organic matter (SOM) to maintain soil structural stability (Pieri 1992). SSI was calculated as follows:  $SSI = 100 \times \frac{SOM (\%)}{Clay (\%) + Silt (\%)}$ . SSI  $\leq 5\%$  indicates a structurally degraded soil, SSI 5 to 7% indicates a high risk of structural degradation, and SSI  $> 7\%$  indicates a low risk (Pieri 1992).

We compiled other auxiliary data from databases and the literature for each trial site, including agroecological zone (AEZ), climate zone, soil type, and rainfall (total annual and crop growing season rainfall). Five AEZs (highland, humid, sub-humid, semi-arid, and arid) as defined by HarvestChoice (2009) were adopted. Wherever available, the soil type of each site was extracted from the site description in the original report. Given the transitory nature of soil classification, we cross-checked all reports of soil type against the names in the third edition of the World Reference Base (WRB) for soil resources (IUSS Working Group WRB 2014). We assigned soils classified according to other systems (e.g., USDA or local systems) to the WRB group through *pro parte* matching. For sites where soil types were not reported, information was extracted from the harmonized Soil Atlas of Africa (Jones et al. 2013). In cases where soil types were not provided, the soil types were deduced from the Soil Atlas based on the geographic coordinates of the sites reported in the publications. The designated soil types represented the dominant soils at the study sites.

### 2.3 Analytical framework

The first part of the analysis focused on defining the empirical distribution of yield response to N, P, and K, agronomic efficiency (AE) and partial factor productivity (PFP) to provide baselines against which future improvements in nutrient use efficiency can be judged. Yield responses were calculated as the differences between the NPK yield ( $Y_{NPK}$ ) and the nutrient-limited yield ( $Y_l$ ) on the same site, year and season following similar analyses on maize (e.g., Rurinda et al. 2020) and rice (e.g., Xu et al. 2019). Accordingly, response to N =  $Y_{NPK} - Y_{PK}$ ; response to P =  $Y_{NPK} - Y_{NK}$ ; and to K =  $Y_{NPK} - Y_{NP}$ .

The AE more closely reflects the impact of the applied nutrients and integrates the recovery efficiency and physiological use efficiency (Ladha et al. 2005). It is a more important measure than PFP for decision-making concerning fertilizer

use. Following the approach used for nutrient omission trials (e.g., Kurwakumire et al. 2015), AE was calculated as follows:  $AE = \left( \frac{Y_{NPK} - Y_O}{N_x} \right)$  where  $Y_{NPK}$  is the grain yield (in  $\text{kg ha}^{-1}$ ) in the NPK treatment,  $Y_O$  is the yield (in  $\text{kg ha}^{-1}$ ) in the omission plot (in  $\text{kg ha}^{-1}$ ) for the nutrient in question, and  $N_x$  is the nutrient application rate of the nutrient in question (in  $\text{kg ha}^{-1}$ ). AE estimates may be biased when applied to multi-year experiments due to the residual effects of nutrients applied in previous seasons. Therefore, AE was calculated only for the first-year data in all trials. When comparing NPK applied, we used the PFP as the nutrient use efficiency indicator. The PFP was calculated as follows:  $PFP = \frac{GY}{N_x}$  where  $GY$  is the grain yield (in  $\text{kg ha}^{-1}$ ), and  $N_x$  represents the N, P, or K input from inorganic fertilizer (in  $\text{kg ha}^{-1}$ ). The PFP is a broader measure of nutrient use efficiency than AE because it constitutes an aggregate efficiency index that includes contributions to crop yield derived from the uptake of indigenous soil nutrients, the uptake efficiency of applied nutrients, and the efficiency with which the nutrient acquired by the plant is converted to grain yield (Dobermann 2005). The N, P, and K input from manure was not taken into account due to the uncertainty of estimating nutrient mineralization rates of manure and the short duration of the studies including manure application.

Variable N:P:K ratios of applied nutrients from various studies can potentially affect nutrient-specific yield responses and nutrient use efficiencies. The N:P:K application ratios for rice were within a narrow band of 1: (0.15 – 0.18): (0.44 – 0.50) and had insignificant effects on the performance indicators evaluated. However, the N:P:K ratios varied extensively for maize NOTs. To evaluate the influence of nutrient application ratios on nutrient use efficiencies, the maize data was separated into seven representative N:P:K ratio categories, which formed the basis for disaggregated assessment of nutrient ratios on yield response, AE and PFP. The nutrient ratio categories were as follows: (i) 1:0.18:0.3; (ii) 1:0.27:0.27; (iii) 1:0.27:0.40; (iv) 1:0.30:0.60; (v) 1:0.33:0.33; (vi) 1:0.36:0.36; and (vii) 1:1:1.

Uncertainty around the estimated values was represented by 95% confidence intervals (CIs). In situations where we could not apply a model, we calculated the 95% CIs using bias-corrected bootstrapping with 9999 replicates. Preliminary diagnostic analyses indicated that none of the response variables was symmetrically distributed. Therefore, we focused the interpretation of our results on the empirical quartiles and the % CV. The lower quartile (Q1) represents the midpoint of values that fall between the smallest and the median of the distribution of the analyzed variable. The median (Q2) represents the midpoint of the entire frequency distribution. The upper quartile (Q3) represents the midpoint of values that fall between the median and the highest value. In asymmetric distributions, the median is preferred because it always falls closest to the mode.

In the context of sustainable intensification, one of the most commonly used measures of production risk is spatio-temporal variability, which is usually indexed by the coefficient of variation (CV). A larger CV reflects more variability and hence greater production risk (Kiwia et al. 2019). Therefore, we calculated the CV and its bootstrapped 95% confidence interval. Another measure of production risk is downside risk, which can be measured either as the number of years or sites for which yields are below a target yield (Kiwia et al. 2019). We estimated the downside risk as the probability of yields falling below a prescribed yield target for maize and rice. In the case of maize, we evaluated the probability of exceeding the African Green Revolution target yield of 3 Mg ha<sup>-1</sup> for the various treatments. In the case of rice, the target yields were 5–9 Mg ha<sup>-1</sup> in irrigated and rainfed lowland and 5–7 Mg ha<sup>-1</sup> in rainfed upland rice (Saito et al. 2019). Accordingly, we estimated the probability of exceeding the yield targets of 5 Mg ha<sup>-1</sup> in rice. We evaluated the downside risks of yield response to N, P, and K as the probability of the yield difference between NPK and treatment ( $Y_{NPK} - Y_T$ ) falling below 0. As such, we calculated the risks of "no response" to applied N, P, and K as the probability of  $Y_{NPK} - Y_{PK} < 0$ ,  $Y_{NPK} - Y_{NK} < 0$  and  $Y_{NPK} - Y_{NP} < 0$ , respectively. We also conducted stochastic dominance analysis — a non-parametric risk analysis tool often used in decision theory. It refers to situations where one probability distribution over outcomes can be ranked as superior to another. This mainly involves plotting the cumulative probability distribution of the outcome variable (Sileshi et al. 2010). A cumulative distribution function  $X$  is said to dominate  $Z$  in the first order if the distribution of  $X$  lies anywhere to the right of the cumulative distribution of  $Z$ . We used this method to estimate the probability ( $\phi$ ) of exceeding a target value of grain yields.

We analyzed the effects of genotype, management, and environmental variables on yield response using linear mixed models, where nutrient management and environmental variables were entered as the fixed effects and one or more variables used as the random effect. To accommodate imbalances in sample sizes, we used the Kenward–Roger method for approximating the degrees of freedom (Spilke et al. 2005). Various models were tested by adding or removing variables until an optimal model was achieved. Improvement in model fit was examined at each step using Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC). As a rule of thumb, changes in BIC (differences between BICs of two models) of 2 to 6 provide weak evidence favoring the more complex model, while differences >10 provide very strong evidence favoring the more complex model. The main effects were country (C), soil type (S), agroecological zones (A), treatment (T), and variety (V) represented by maturity groups. The models were modified depending on the availability of

explanatory variables. For example, in the case of rice the data were hierarchical, and the most complex model was:

$$y_{ijkl} = \mu + C_i + A_j + S_j + T_k + V_l + (S \times T)_{jk} + (T \times V)_{kl} + \epsilon_{ijkl}$$

where  $\mu$  is the intercept, which represents the grand mean of the response variable across all explanatory variables and  $\epsilon_{ijkl}$  is the residual (a random error term). Here  $\mu$  was set as a random intercept where "country" was used as the subject specifying that data from one country are more correlated than data from another country. LMM was also applied to a subset of the data involving the combined application of NPK with micronutrients, lime, or manure. These combinations were tested on seven sites in four countries across SSA. The sites were Sidindi in Kenya, Kasungu, Nkhata Bay and Tuchila in Malawi, Kiberashi and Mbinga in Tanzania, and Pampaida in Nigeria. In all seven sites, data were available for the no-input control, NPK, NPK + SMN and NPK + manure, whereas data for NPK + lime was available for all sites except Mbinga and Pampaida. In both the large dataset and the subset analyses, planned comparisons were used to determine the magnitude and direction of differences in response between the NPK (used as the control) and all other treatments. Planned comparisons focus on a few theoretically sensible comparisons, and therefore have the advantage of increased statistical power relative to the conventional "all possible comparison." Dunnett's test was applied because it is designed for comparing treatment groups with a control group and adjusts  $P$ -values to overcome the multiplicity problem.

We used machine learning algorithms to explore the genotypic, environmental, and management variables that influence yield response and agronomic efficiencies of applied nutrients. We used random forest (RF) ensemble models to rank the importance of each of the variables and to predict the yield responses (Breiman 2001). The RF algorithm creates and merges several decision trees to get the most reliable forecast. Sets of 22 and 25 predictor variables were used for maize and rice, respectively. These were variety (maturity type), AEZ, total rainfall, solar radiation, minimum temperature ( $T_{min}$ ), maximum temperature ( $T_{max}$ ), soil type, soil organic carbon (SOC), total N, C:N ratio, clay content, sand content, soil pH, total N, available P, exchangeable K, Ca, Mg, Ca:Mg, Ca:K, Mg:K ratios and soil stability index (SSI), N rate, P rate and K rate. We used the coefficient of determination ( $R^2$ ), cross-validation root mean square of error (RMSE), residual prediction deviation (RPD), and bias for the assessment of model accuracy. To estimate the importance of each variable, predictions based on the data used for the training of the RF model were compared to observations not used in the creation of the trees (i.e., the out-of-bag samples). Then, we created the partial dependence plots (PDPs) for each response variable using the top five influential variables.

### 3 Synthesis

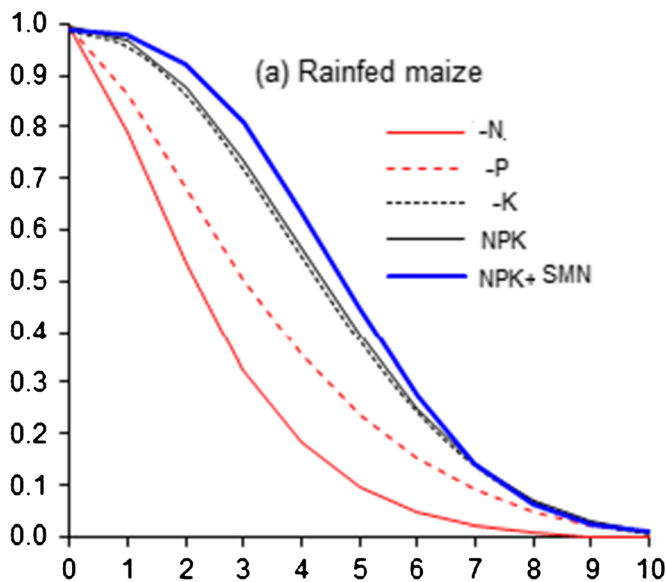
#### 3.1 Overall effects of nutrient applications on yields and NUE

The cumulative frequency distributions of yields (Fig. 2) revealed that the water-limited grain yield ceiling of maize is 10 Mg ha<sup>-1</sup> (at ~88% dry matter); the probability of exceeding this value with either NPK or NPK + SMN was only 0.01. This

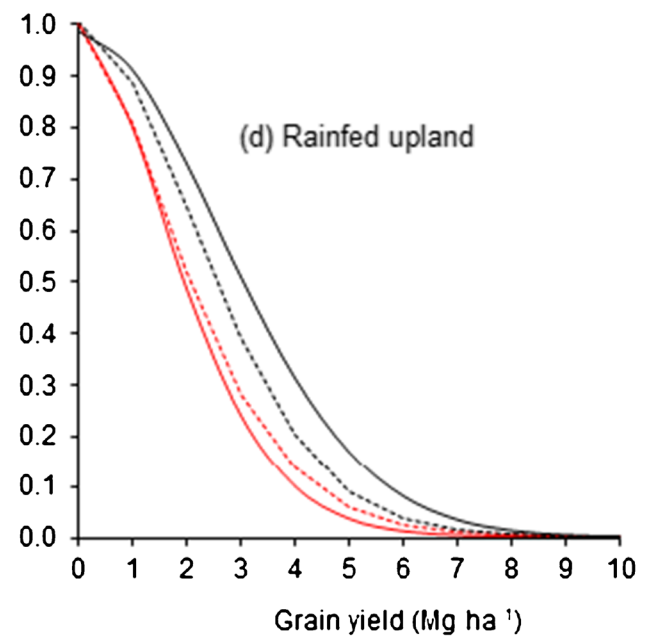
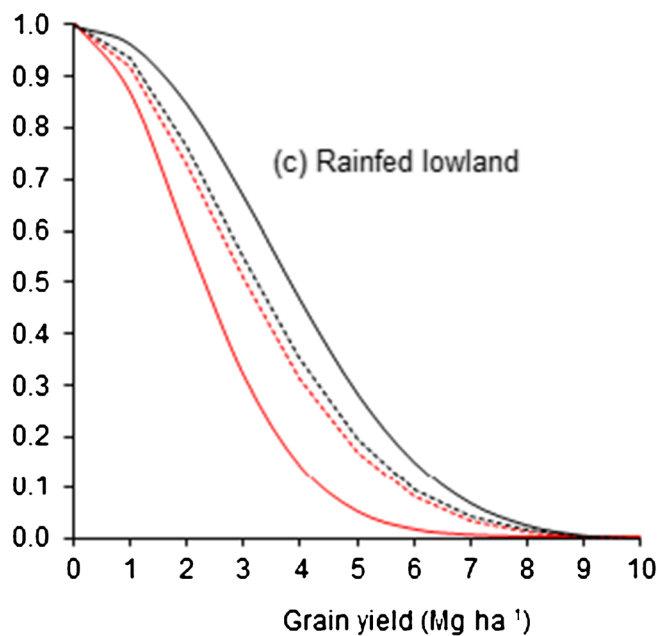
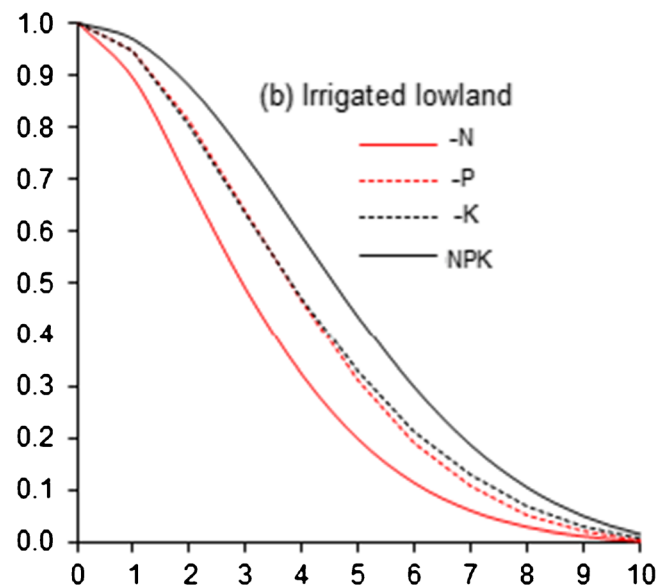
value is slightly higher than the 7–8 Mg ha<sup>-1</sup> reported in earlier analyses (e.g., Kihara et al. 2017; Sileshi et al. 2010). On average, attainable yields of maize with combined application of NPK were 4.1 Mg ha<sup>-1</sup>, which is about two times the current average yields on farmers' fields (~2 Mg ha<sup>-1</sup>; van Ittersum et al. 2013). Unlike maize, the cumulative distribution function of NPK yields in rice stochastically dominated -K yields (Fig. 2).

The overall effects of treatments on grain yields and partial factor productivity of N, P, and K were highly significant ( $P <$

#### Probability of exceeding



#### Probability of exceeding



**Fig. 2** The cumulative probability distribution of grain yields (at 86 to 88% dry matter) of **a** rainfed maize, **b** irrigated lowland rice, **c** rainfed lowland rice, and **d** rainfed upland rice using different combinations of N, P, K, NPK + other macronutrients and micronutrients (NPK+SMN). -N =

PK; -P = NK; -K = NP. The cumulative distribution function of NPK yields is said to dominate yields from treatment X if the distribution of NPK lies to the right without overlapping or crisscrossing.

0.001; Table 1). Although no significant differences were found in maize grain yield between NPK and -K, NPK was superior to -K in terms of partial factor productivities of N and P (Table 1). This indicates that N and P are more efficiently utilized in maize production systems when K is applied. This agrees with earlier findings on the synergistic effects of N and K on yield elsewhere (Hirmiak 2018; Hou et al. 2019; Rietra et al. 2017). While -K, NPK and NPK + SMN were indistinguishable in terms of mean yields (Table 1) and their cumulative probability distributions of yields (Fig. 2), spatiotemporal variability in yield was greatly reduced with NPK + SMN (CV = 43.3%) relative to NPK (CV~49%). The probability of exceeding the African Green Revolution maize yield target of 3 Mg ha<sup>-1</sup> was higher with NPK + SMN ( $\phi = 0.81$ ) than with NPK alone ( $\phi = 0.73$ ; Table 1).

Under irrigation, the rice yield ceiling was ~10 Mg ha<sup>-1</sup> (at ~86% dry matter), while the corresponding value was ~8 Mg ha<sup>-1</sup> in both lowland and upland rainfed rice production systems (Fig. 2). The probability of achieving the

target yields of 7 and 9 Mg ha<sup>-1</sup> was <0.02, and this occurred only on Luvisols. The estimated attainable yield is comparable with attainable yields of 10.8 Mg ha<sup>-1</sup> in Tanzania and 10.3 Mg ha<sup>-1</sup> in Madagascar reported in the GYGA database (GYGA 2021), but higher than the values of 8.3 Mg ha<sup>-1</sup> reported by Niang et al. (2017) for irrigated lowland rice. The rice yield ceilings observed in rainfed lowland and rainfed upland are also higher than the 6.5 and 4.0 Mg ha<sup>-1</sup> reported in Niang et al. (2017). Across the three rice production systems, NPK significantly ( $P < 0.001$ ) increased rice grain yields and partial factor productivities over -N, -P, and -K (Table 1). The partial factor productivities of N and P were significantly higher ( $P < 0.001$ ) with NPK than -K in all rice production systems (Table 1).

The results in Table 1 demonstrate that with the balanced application of NPK fertilizer, grain yields of about 4 Mg ha<sup>-1</sup> are attainable for rainfed maize and rice at scale. This indicates that maize and rice yields can be doubled with the balanced

**Table 1** Grain yield (Mg ha<sup>-1</sup>), coefficients of variation (CV), the probability of failing to achieve a target yield of 3 Mg ha<sup>-1</sup> ( $\phi < 3$ ) and partial factor productivity (kg grain kg<sup>-1</sup> nutrient) of N, P, and K following different fertilizer treatments in maize, irrigated lowland (IL), rainfed lowland (RL), and rainfed upland (RU) rice. †Treatments are: -N, -P, -K, no-input control; -N, omission of N (PK alone); -P, omission of P (NK alone); -K,

omission of K (NP alone); NPK + SMN, combined application of NPK with other macronutrients and micronutrients. ‡Sample size represents site-season (year) combinations. According to Dunnett's test, means followed by \*\*\*, \*\*, and \* are significantly different from NPK means (shaded gray) at the 0.001, 0.01, and 0.05  $\alpha$  levels, respectively, while ns, not significantly different from NPK means.

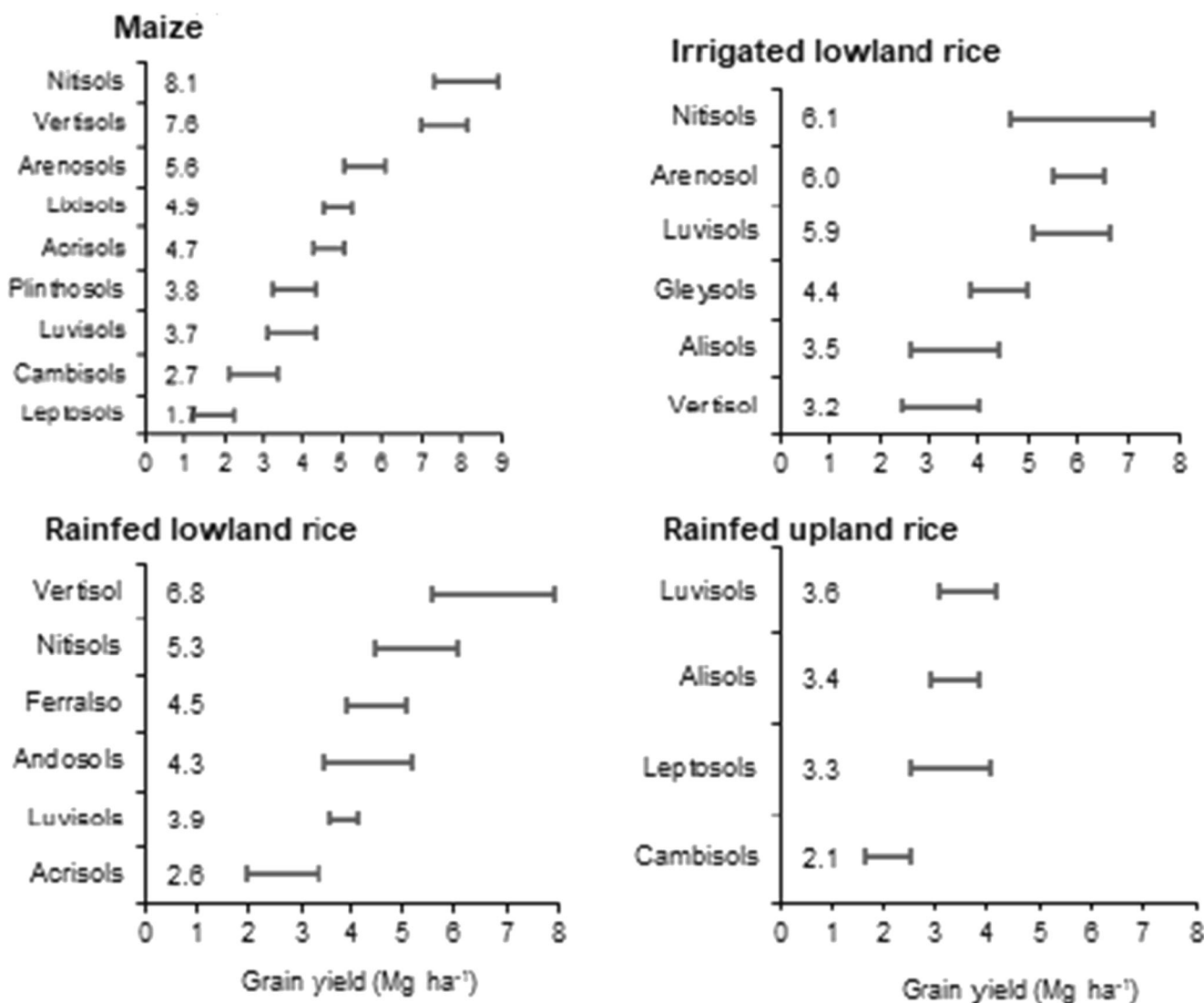
Crop/ system	Treatment <sup>†</sup> (sample size) <sup>‡</sup>	Mean grain yield	Production risk		Partial factor productivity		
			CV	$\phi < 3$	N	P	K
Maize	-N, -P, -K (1521)	1.7***	77.1	0.77	--	--	--
	-N (1374)	2.0***	69.5	0.67	--	53.8***	37.9***
	-P (1299)	2.9***	67.4	0.50	25.0***	--	57.7***
	-K (1308)	3.9 <sup>ns</sup>	49.7	0.28	33.0*	110.9*	--
	NPK (1580)	4.1	49.0	0.27	34.9	117.8	82.1
	NPK + SMN (1026)	4.2 <sup>ns</sup>	43.3	0.19	36.7*	125.6*	86.8*
IL rice	-N (323)	3.5***	60.3	0.55	--	132.1***	43.8***
	-P (321)	4.3***	53.2	0.40	24.6***	--	51.9***
	-K (323)	4.4***	55.2	0.41	25.1***	161.0***	--
	NPK (327)	5.0	49.7	0.27	28.3	182.3	59.9
RL rice	-N (510)	2.6***	56.7	0.68	--	118.4***	44.5***
	-P (508)	3.4***	54.6	0.49	25.0***	--	55.5***
	-K (506)	3.6***	51.8	0.45	26.4***	157.3***	--
	NPK (512)	4.1	47.2	0.35	30.8	182.3	68.3
RU rice	-N (175)	2.3***	63.0	0.78	--	103.4***	40.0***
	-P (175)	2.5***	66.0	0.75	19.7***	--	43.6***
	-K (175)	2.9***	58.9	0.64	22.7***	129.5**	--
	NPK (175)	3.4	56.1	0.47	27.1	154.6	60.1



application of NPK. The mean rice yields achieved with NPK (Table 1) are higher than those reported on farmers' fields (Tanaka et al. 2017) in irrigated lowland (2.2–5.8 Mg ha<sup>-1</sup>), rainfed lowland (1.1–5.2 Mg ha<sup>-1</sup>), and rainfed upland (1.0–2.5 Mg ha<sup>-1</sup>) rice across SSA. The attainable yields, however, significantly ( $P < 0.001$ ) varied with soil type (Fig. 3). The highest and lowest maize yields were achieved on Nitisols (8.1 Mg ha<sup>-1</sup>) and Leptosols (1.7 Mg ha<sup>-1</sup>), respectively. In irrigated and rainfed lowland rice, the highest yields were recorded on Nitisols (6.1 Mg ha<sup>-1</sup>) and Vertisols (6.8 Mg ha<sup>-1</sup>), respectively (Fig. 3). The highest yield of rainfed upland rice (3.6 Mg ha<sup>-1</sup>) was attained on Luvisols, but this did not significantly differ from yields achieved on other soils. In contrast, Vertisols gave lowest yield for irrigated rice, while they gave the highest yield in rainfed lowland rice.

On a subset of the sites where NPK was applied in combination with other macronutrients and micronutrients or manure, grain yields and partial factor productivity of N, P, and K were significantly ( $P < 0.001$ ) higher than with NPK alone (Table 2). NPK + manure achieved the highest yield increase over NPK (24.2%) and the no-input control (127.8%). With a CV of ~49%, the lowest spatiotemporal variability was recorded with NPK + manure (Table 2). The mean increase in grain yield with NPK + SMN (18.2%) over NPK was lower than the 25% increase reported in Kihara et al. (2017). The highest PFPN, PFP, and PFPK were recorded in NPK + manure, which were significantly higher than in NPK alone (Table 2).

The trends in Fig. 3 suggest that soil type is one of the key determinants of the large-scale variability in yield. Earlier analyses have also identified soil type as a major determinant of indigenous soil nutrient supply, crop yield response, and



**Fig. 3** Variations in maize and rice grain yields with soil type and NPK treatment. Horizontal bars represent the 95% confidence limits. Two or more soils are deemed significantly different if their 95% confidence limits

are not overlapping. Values on the y-axis represent the mean yield (Mg ha<sup>-1</sup>) per soil type.

**Table 2** Mean maize grain yields ( $\text{Mg ha}^{-1}$ ), coefficients of variation (CV), the probability of failing to achieve a target yield of  $3 \text{ Mg ha}^{-1}$  ( $\phi < 3$ ) and partial factor productivity ( $\text{kg kg}^{-1}$  nutrient) of N, P, and K on sites where a combination of NPK, other macronutrients, micronutrients, lime and manure were compared. †Treatments are: -N, -P-K, no-input control; -N, omission of N (PK alone); -P, omission of P (NK alone); -K, omission of K (NP alone); NPK

Treatment† (sample size)‡	Mean grain yield	Production risk		Partial factor productivity		
		CV	$\phi < 3$	N	P	K
-N, -P, -K (349)	1.8***	78.2	0.84	--	--	--
-N (211)	2.2***	73	0.74	--	74.3***	37.2***
-P (135)	2.9*	66.3	0.64	30.1 <sup>ns</sup>	--	48.8 <sup>ns</sup>
-K (138)	3.0 <sup>ns</sup>	62.5	0.61	31.1 <sup>ns</sup>	100.9 <sup>ns</sup>	--
NPK (385)	3.3	58.1	0.50	34.2	112.1	56.1
NPK + lime (160)	3.5 <sup>ns</sup>	63.6	0.53	36.2 <sup>ns</sup>	117.4 <sup>ns</sup>	58.8 <sup>ns</sup>
NPK + SMN (187)	3.9*	54.8	0.34	38.8*	128.0*	64.1*
NPK + manure (247)	4.1***	49.4	0.34	41.1***	135.5***	67.8***

+ SMN, combined application of NPK with other macronutrients and micronutrients. ‡Sample size represents site-season (year) combinations. Means followed by \*\*\* and \* are significantly different from NPK means at 0.001 and 0.05  $\alpha$  levels, respectively, while ns, not significantly different according to the Dunnett's test.

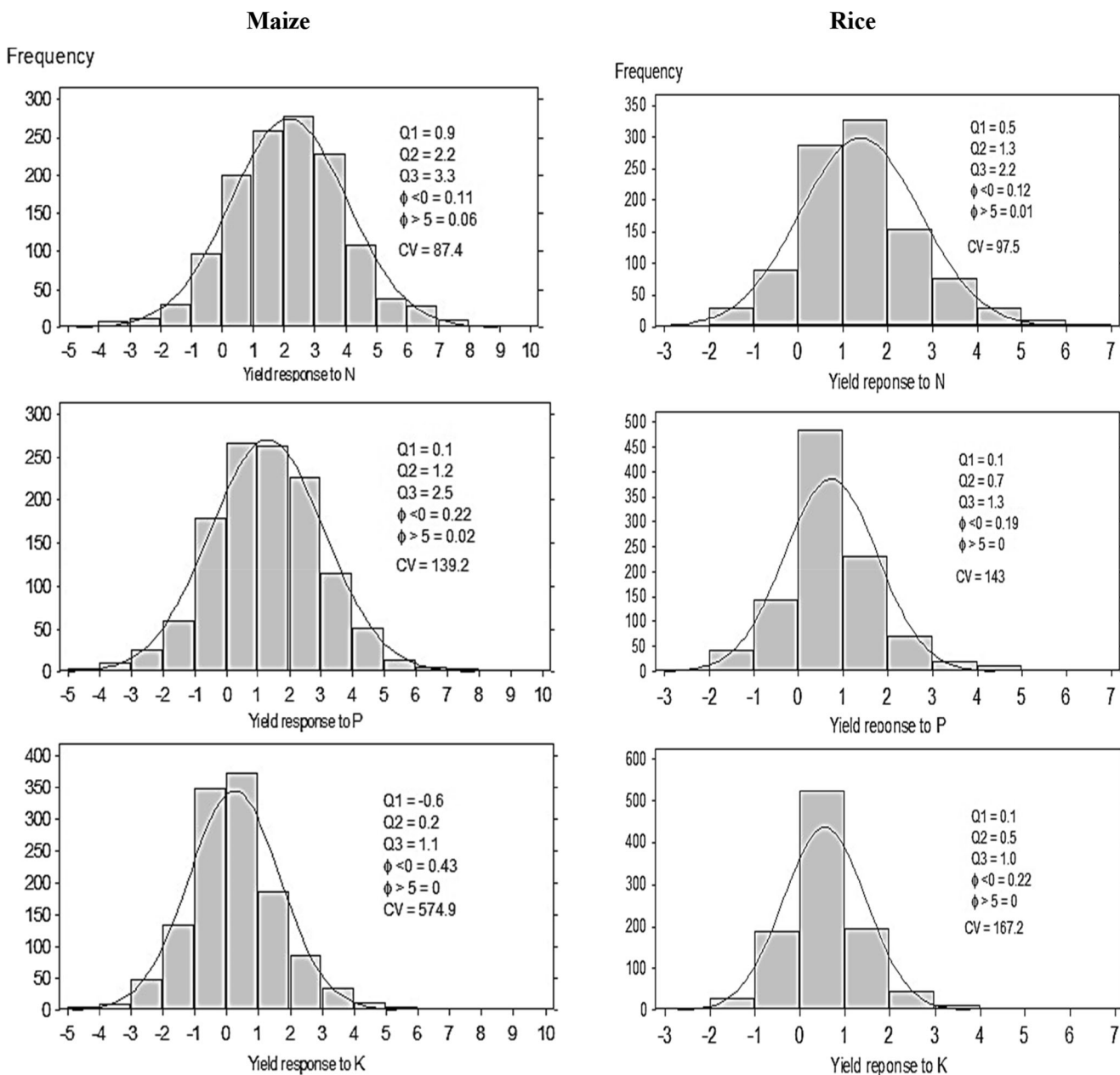
input use efficiency (Kihara et al. 2017; Sileshi et al. 2010). Many soil properties are related to clay mineralogy and texture. Clay minerals play an important role in the supply, retention and fixation of nutrients and, consequently, crop yield responses to nutrient applications. Generally, soils with low-activity and 1:1 clay lattice (e.g., Acrisols, Ferralsols, Lixisols, Nitisols and Plinthosols) have low CEC and poor capacity to supply nutrients compared to high-activity clays with 2:1 lattice (e.g., Alisols, Cambisols, Fluvisols, Luvisol and Vertisols). Soils that contain 2:1 clay may fix  $\text{NH}_4$  and K within their lattice structures, while highly weathered soils rich in 1:1 lattice and amorphous clay minerals have high levels of free Al and Fe with a high P-fixing capacity (Batjes 2011). The consistently high yields of maize and rice on Vertisols and Nitisols could be attributed to their high clay content (>30%), SOM and high water-holding capacity (IUSS Working Group WRB 2014). The strongly acidic conditions and P sorption on Alisols, Acrisols and Ferralsols (Batjes 2011) may also result in low N and P use efficiencies. The omission of P led to a 50% reduction in maize yield on the acidic Ferralsols in eastern Kenya (Kihara and Njoroge 2013). AEP is expected to be low on soils with inherently high plant-available P or high P retention, such as Andosols, Alisols, Acrisols, and Ferralsols (Batjes 2011). The low maize yields observed on Leptosols (Fig. 3) may be associated with their poor physical characteristics. Leptosols are shallow soils rich in coarse fragments, making them susceptible to erosion (IUSS Working Group WRB 2014). This may also explain the low yield response to P and AEP on Leptosols (Supplementary Fig. S2). Although Arenosols are sandy and have poor water and nutrient holding capacity, they had higher

maize and rice yields and yield responses than many other soil types.

### 3.2 Spatial variability in yield response and agronomic efficiency

This analysis established the empirical distributions (Figs. 4 and 5) and expected values (Table 3) of yield responses to N, P, and K and agronomic efficiencies. In both maize and rice, N accounted for the largest yield response (Table 3). This is consistent with earlier observations that N is the most yield-limiting nutrient, followed by P and K in SSA (e.g., Saito et al. 2019). Based on the median values in Fig. 4, we estimate yield responses to N, P, and K in the ratio of 11:6:1 in maize and 2.6:1.4:1 in rice. The ratio found for rice was similar to ratios found for irrigated rice in China (Xu et al. 2019). The higher yield response to N in maize compared to rice could be attributed to the differences in their photosynthetic pathways. Photosynthetic N use efficiency is known to be higher in maize (a C4 plant) than in rice (a C3 plant) (Makino et al. 2003). Due to the different carbon fixation mechanisms, C4 plants such as maize have a higher photosynthesis efficiency than C3 plants such as rice (Wang et al. 2012). C3 photosynthesis only uses the Calvin cycle to fix  $\text{CO}_2$  catalyzed by ribulose-1,5-bisphosphate carboxylase (Rubisco), which takes place inside the mesophyll cell's chloroplast. For C4 plants such as maize (NADP-ME subtype), photosynthetic activities are partitioned between mesophyll and bundle sheath cells that are anatomically and biochemically distinct (Wang et al. 2013).

The CVs indicate that maize yield response to K is 6–9 times more variable than the response to N (Table 3). The high



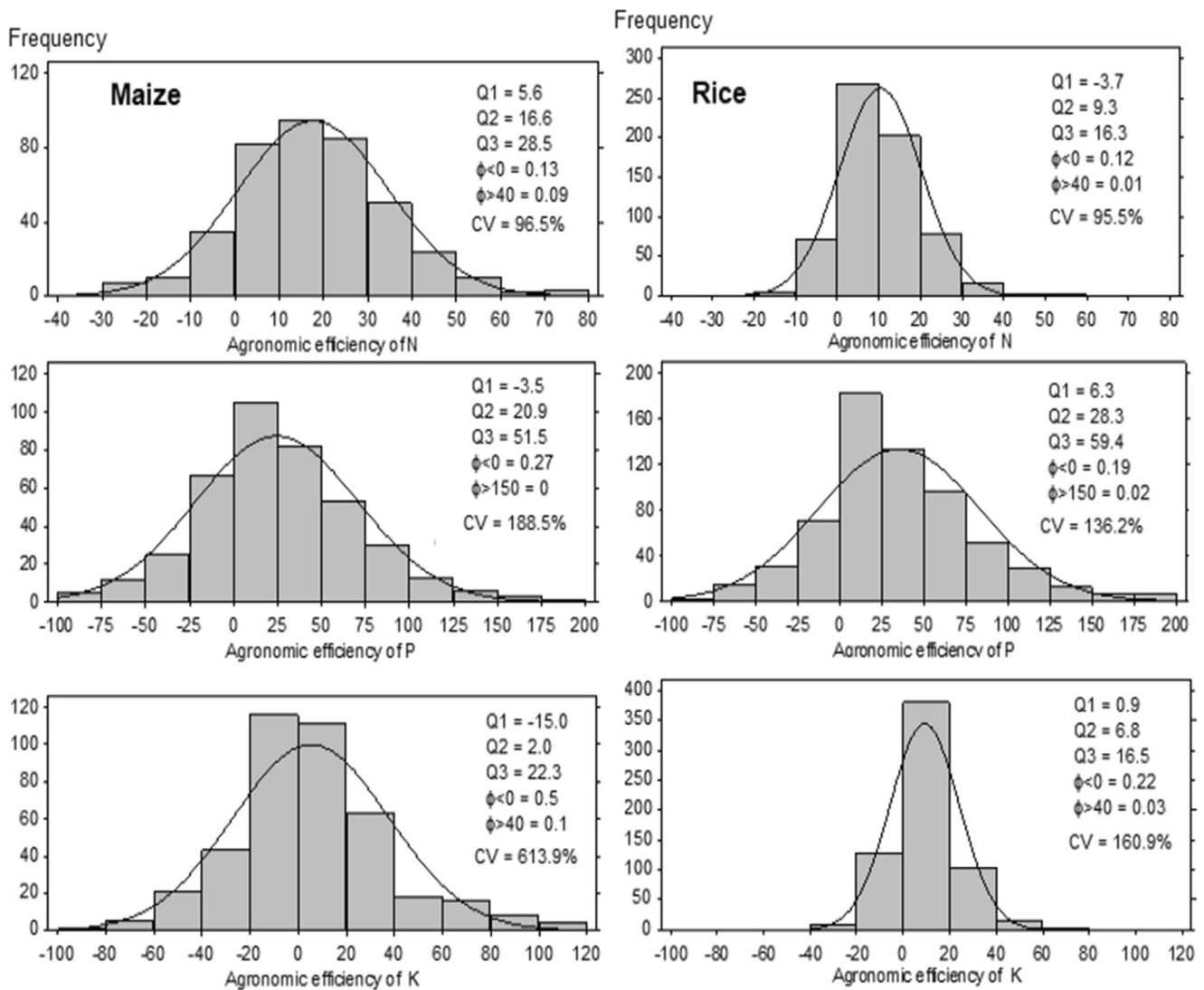
**Fig. 4** Frequency distributions of maize and rice yield responses (Mg grain ha<sup>-1</sup>) to N, P, and K across sites. Q1 is the first quartile, Q2 is the median, Q3 is the third quartile,  $\phi$  is the probability of values falling below (<) or exceeding (>) a given level and CV is the coefficient of

variation (%). For maize, sample sizes were 1302, 1225, and 1237 for yield responses to N, P, and K, respectively. The respective sample sizes in rice (production systems combined) were 647, 642, and 647 for N, P, and K.

variability in response to K clearly emphasizes the need for site-specific K application recommendations. It also underscores the need for a better understanding of conditions under which yield responses to K are expected.

In maize, the probabilities of no response ( $\phi < 0$ ) to N, P, and K were 0.11, 0.22, and 0.43, respectively (Fig. 4). In the case of rice, the corresponding probabilities were 0.12, 0.19, and 0.22, respectively (Fig. 4). The average maize yield responses to N, P, and K with NPK + SMN were not significantly different from responses with NPK alone (Table 3).

However, spatial variability in N and P responses was lower with NPK + SMN than NPK alone (Table 3). The opposite effect was observed with response to K; the 95% confidence intervals of the CV were wider under NPK + SMN (563–1829%) compared with NPK (388–1455%). With NPK + SMN, yield response to N increased by 80–400% on Luvisols, Leptosols, and Vertisols compared to NPK alone. Agronomic efficiency of P was also significantly improved with NPK + SMN (36.5 kg increase in grain kg<sup>-1</sup> P) over NPK alone (24.5 kg increase in grain kg<sup>-1</sup> P). P response



**Fig. 5** Frequency distributions of the agronomic efficiency (kg grain increase  $\text{kg}^{-1}$ ) of applied N, P, and K in maize (left panel) and rice (right panel). Smooth lines represent the normal probability distribution

of the variable. Q1 is the first quartile, Q2 is the median, Q3 is the third quartile,  $\phi$  is the probability of values falling below (<) or exceeding (>) a given level, and CV is the coefficient of variation (%).

was higher with NPK + SMN than NPK alone on most soils except Acrisols. On the other hand, K response was lower with NPK + SMN than NPK alone on Arenosols, Lixisols, Nitisols, and Plinthosols. This indicates that the effects of the other macronutrients and micronutrients on the agronomic efficiency of N, P, and K are location-specific.

Rice yield response to N significantly ( $P < 0.001$ ) varied with production systems (Table 3), but responses to P and K did not vary significantly. The yield responses to P recorded in this study (Table 3) are strikingly similar to yield response of irrigated rice to P ( $0.9 \text{ Mg ha}^{-1}$ ) in a large number of on-farm nutrient omission trials in the major rice-producing regions of China (Xu et al. 2019). K yield responses were 2–3 times higher in rice than in maize. This is probably because of differences in the soil available K status and K uptake requirements. For example, a  $1 \text{ Mg ha}^{-1}$  rice straw harvest requires an annual uptake

of  $16.6 \text{ kg K ha}^{-1}$  in lowland rice and  $23.8 \text{ kg K ha}^{-1}$  K in upland rice, while a  $1 \text{ Mg ha}^{-1}$  maize straw harvest requires  $12.9 \text{ kg K ha}^{-1}$  (Rietra et al. 2017). On average, 68–90% of the K taken up by rice is stored in the straw; K contents in straw typically increase with K supply (Ye et al. 2019). Higher response to K in rice could also be attributed to the relatively higher N rates applied, especially in irrigated rice. Generally, rice yield response to K increases with an increase in N application rates (Hou et al. 2019).

Table 3 summarizes the estimated values of yield response and agronomic efficiency, and their uncertainty in the different cropping systems. Figure 4 and Supplementary Fig. S2 provide the empirical distributions and variations with soil type. These values may be used as baselines against which future improvements in response and AE can be judged. Even though the N rates applied were the same, agronomic

**Table 3** Estimates of yield responses (in Mg ha<sup>-1</sup>) to N, P, and K, agronomic efficiencies (kg increase in grain kg<sup>-1</sup>) and their spatial variability (expressed in CV%) in maize and irrigated lowland (IL), rainfed lowland, and rainfed upland (RU) rice cropping systems. Figures in parentheses are bias-corrected 95% CIs.

Crop	Mean			CV (%)		
	N	P	K	N	P	K
<b>Yield response</b>						
Maize with NPK alone	2.2 (2.0, 2.4)	1.0 (0.9, 1.2)	0.2 (0.1, 0.4)	96.8	184.0	619.1
Maize with NPK + SMN	2.1 (2.0, 2.2)	1.2 (1.0, 1.3)	0.2 (0.1, 0.3)	92.5	169.9	875.8
IL rice	1.8 (1.6, 2.0)	0.8 (0.6, 0.9)	0.6 (0.5, 0.8)	78.7	139.8	169.1
RL rice	1.4 (1.3, 1.6)	0.7 (0.6, 0.9)	0.6 (0.5, 0.7)	94.7	151.2	166.8
RU rice	1.0 (0.9, 1.2)	0.9 (0.8, 1.1)	0.5 (0.4, 0.6)	106.6	107.3	136
<b>Agronomic efficiency</b>						
Maize with NPK alone	17.6 (15.9, 19.3)	24.5 (19.9, 28.9)	5.3 (2.1, 8.5)	96.5	188.3	613.9
Maize with NPK + SMN	16.7 (15.7, 17.6)	36.5 (32.3, 40.7)	3.3 (1.3, 5.4)	92.2	187.7	996.3
IL rice	9.7 (8.7, 10.8)	28.1 (22.8, 33.7)	7.4 (5.6, 9.1)	76.9	138	166.2
RL rice	11.3 (10.1, 12.5)	35.0 (29.3, 40.6)	10.2 (8.3, 12.1)	98.5	148.3	165.1
RU rice	8.8 (7.2, 10.3)	45.0 (37.2, 52.7)	9.5 (7.4, 11.6)	106.2	107.7	135.9

efficiencies for N were lower in rainfed rice than in maize (Table 3). This is probably because N is more efficiently utilized by maize, a C4 plant (Makino et al. 2003). In contrast, applied K was used with greater efficiency in rice than in maize production systems, although higher rates of K were applied in rice cropping systems (Table 3).

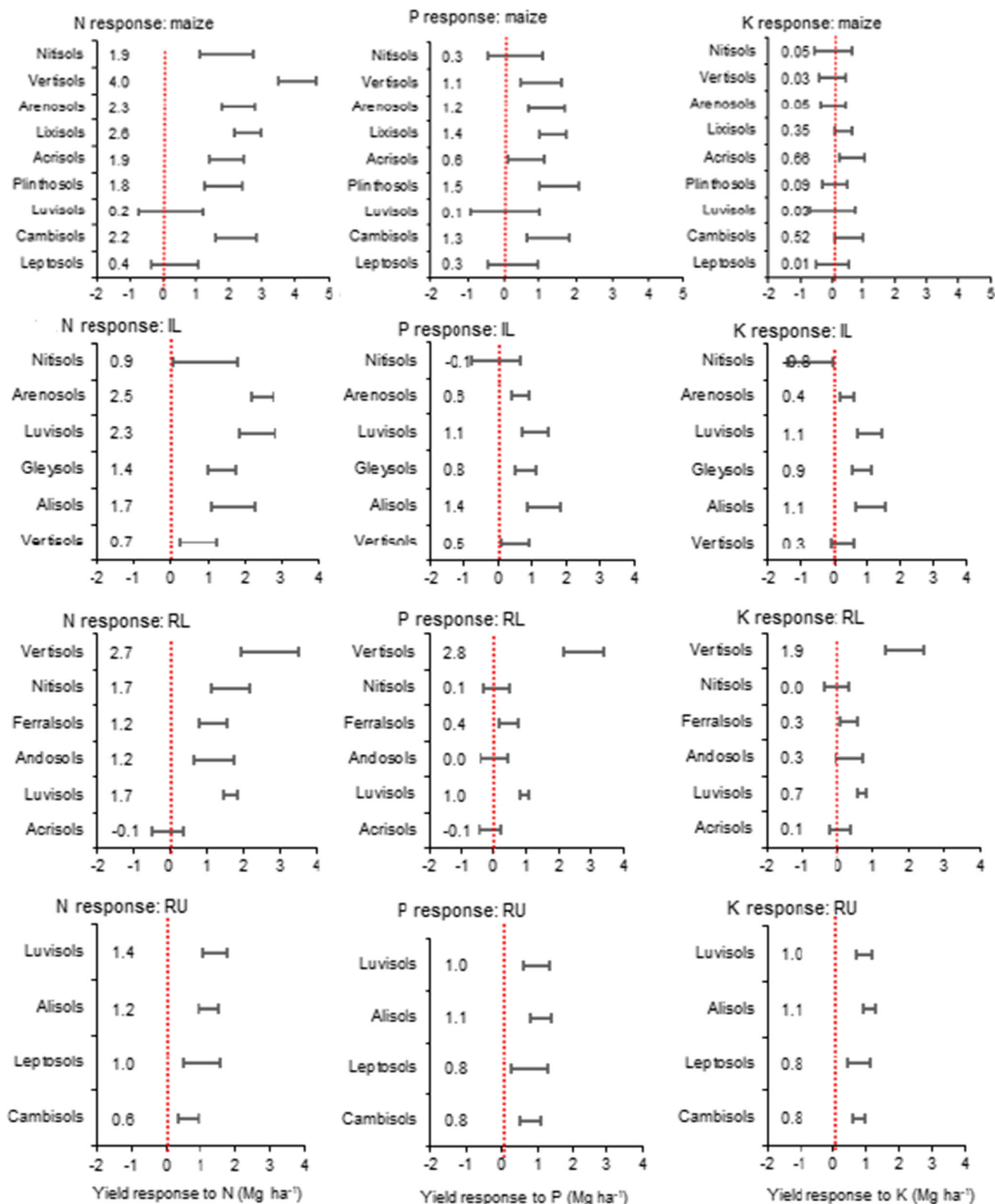
The mean AEN recorded in this analysis is comparable with values reported elsewhere for maize (Ten Berge et al. 2019) and rice (Chivenge et al. 2021). The AEP and AEK of maize recorded in this analysis (Table 3) are also comparable with the range of AEP values (23–26 kg grain increase kg<sup>-1</sup> P) and AEK values (0.9–5.4 kg grain increase kg<sup>-1</sup> K) reported in Ten Berge et al. (2019) and Dhillon et al. (2019). However, our results (Supplementary Fig. S2) provide additional evidence for significant variation with soil type and production system.

In both maize and rice cropping, soil type followed by agroecological zone and maturity period of varieties accounted for the largest proportion of explained variation in N, P, and K responses (Supplementary Table S4). This is consistent with the results of farm surveys, which show differences in rice yield between the agroecological zones (Tanaka et al. 2017). Mean maize yield response to N was significantly ( $P = 0.0012$ ) higher in humid (2.1 Mg ha<sup>-1</sup>) and subhumid (1.9 Mg ha<sup>-1</sup>) sites than in semi-arid (1.4 Mg ha<sup>-1</sup>) sites. Similarly, maize yield responses to P and K were significantly ( $P < 0.001$ ) higher in humid sites than in subhumid and semi-arid sites. Maize and rice yield responses to N significantly ( $P < 0.001$ ) varied with soil types (Fig. 6) and maturity periods of varieties. In both crops, yield responses to N were significant

and positive ( $YR > 0$  Mg ha<sup>-1</sup>) on all soil types; the exception being on Luvisols and Leptosols in maize and Acrisols in rainfed lowland rice (Fig. 6). The highest maize response to N (4.0 Mg ha<sup>-1</sup>) was recorded on Vertisols, while the lowest (0.2 Mg ha<sup>-1</sup>) was recorded on Luvisols, which was significantly lower than all other soils, except Leptosols (Fig. 6), as indicated by the non-overlapping 95% CI. Rice yield response to N was highest on Arenosols (2.4 Mg ha<sup>-1</sup>) in irrigated lowland, Vertisols (2.7 Mg ha<sup>-1</sup>) in rainfed lowland, and Luvisols (2.7 Mg ha<sup>-1</sup>) in rainfed upland rice (Fig. 6).

Maize and rice yield responses to P were significantly higher than zero on most soil types except Nitisols, Luvisols, Leptosols, Acrisols, and Andosols (Fig. 6). The highest maize yield response to P (1.5 Mg ha<sup>-1</sup>) was recorded on Plinthosols, while the lowest response (0.1 Mg ha<sup>-1</sup>) with the largest spatial variability was recorded on Luvisols. The highest mean yield response to K (0.7 Mg ha<sup>-1</sup>) with the smallest spatial variability was recorded on Acrisols, while the lowest (0.01 Mg ha<sup>-1</sup>) was on Leptosols (Fig. 6). Maize yield response to K was not significant on most soils except Lixisols, Acrisols, and Cambisols.

In irrigated lowland rice, the highest yield response to N was recorded on Arenosols (2.5 Mg ha<sup>-1</sup>), while the lowest was on Vertisols (0.7 Mg ha<sup>-1</sup>). The opposite was observed in rainfed lowland, where the highest yield response to N was recorded on Vertisols (2.7 Mg ha<sup>-1</sup>). These differences could be due to differences in management and water relations between irrigated and rainfed lowlands. Yield response to P was higher on Vertisols and Alisols in rice production systems (Fig. 6). Although Vertisols have good chemical fertility, their physical



**Fig. 6** Variations in yield response to N, P, and K by soil type in maize, irrigated lowland (IL), rainfed lowland (RL), and rainfed upland (RU) rice. Horizontal bars represent the 95% confidence limits. Numbers on the y axis represent mean yield responses for each soil type. The red dotted vertical line represents the point where there was no yield gain or loss

( $Y_{NPK} = Y_i$ ) due to treatment relative to NPK. The 95% confidence limits falling above that line indicate significant response to the nutrient in question. Calculations are as follows: response to N =  $Y_{NPK} - Y_{PK}$ ; response to P =  $Y_{NPK} - Y_{NK}$ ; response to K =  $Y_{NPK} - Y_{NP}$ .

characteristics, notably their complex water relations, pose management challenges (IUSS Working Group WRB 2014). In rainfed upland rice, response to applied P was highest on Alisols (Fig. 6). This is probably because applied P alleviated the constraints due to the high P-fixing capacity on these soils. Alisols are strongly acidic and suffer from aluminum toxicity, P sorption, and poor water relations (Batjes 2011; IUSS Working Group WRB 2014). Responses to K were significant and positive on most soils except Nitisols, Vertisols, and Acrisols in rice cropping systems (Fig. 6). The trends in agronomic efficiency (Supplementary Fig. S2) generally followed the trends in yield response (Fig. 6).

Although the highest grain yields of maize and irrigated rice were recorded on Nitisols, yield responses to P and K were consistently low on Nitisols (Fig. 6). The low yield response in maize and irrigated rice to K on Nitisols and Vertisols may be partly caused by the naturally high K reserves (Elephant et al. 2019) and interactions between applied K and the exchangeable Mg, Ca, and Na (Rietra et al. 2017).

Beyond the crop and environmental factors affecting agronomic nutrient use efficiencies, there were significant differences in maize yield responses and agronomic nutrient use efficiencies for various categories of N:P:K application ratios (Table 4). The differences were due to a combination of the different N:P:K application ratios, nutrient application rates, and the differences in nutrient-specific yield responses at various study sites. Agronomic N and P use efficiencies were low in low-yield-response data sets (1:0.33:0.60 and 1:1:1), irrespective of nutrient application ratios. For the 1:1:1 category, a high application rate of P ( $100 \text{ kg P ha}^{-1}$ ) coupled with the mode of application (broadcasting and incorporation) contributed to the extremely low AEP value. Spot placement of fertilizer P has been shown to result in more efficient crop uptake of applied P compared to broadcasting and incorporation due to the higher concentration of P close to plant roots in spot application compared to in broadcast application (Van der Eijk et al. 2006). The relatively low AEN observed for the 1:1:1 category could also be partly attributed to the lower yield response to applied N due to the broadcast application of a

third of the N applied. Agronomic K efficiency was highest for the 1:0.27:0.27 ratio category, partly due to the lower proportion of K applied (Table 4). The results underscore the importance of accounting for nutrient application ratios and nutrient application methods in interpreting trends in agronomic nutrient use efficiencies.

### 3.3 Predictors of yield and yield response

The random forest algorithms provided further insights into the factors associated with the spatial variations in grain yields and responses to N, P, and K in maize and rice. To focus on key results, the top six variables are summarized in Table 5. A complete set of all the variable importance plots is provided in Supplementary Fig. S3 for maize and Supplementary Fig. S4 for rice. The partial dependence plots (PDPs) and predictions of yield, yield response, and agronomic efficiency are given in Supplementary Fig. S5 for maize and Supplementary Fig. S6 for rice.

In maize, exchangeable Ca, Mg, K, pH, soil type, Mg:K and Ca:K ratios were identified as the most influential variables for yield, yield responses, and agronomic efficiency (Table 5). The results are consistent with past studies in SSA (Farina et al. 1992; Lombin 1981; Mtangadura et al. 2017; Roobroeck et al. 2021) that have established correlations between maize yields and exchangeable Ca, Mg, and K. In long-term trials in the northern Nigerian savannah, Lombin (1981) noted depression of maize yield by K, which created unfavorable soil Ca:K and Mg:K ratios.

Rice yields and yield responses to N, P, and K were mainly driven by exchangeable cations and their ratios, rainfall, temperature, solar radiation, soil type, and variety (Table 5). In irrigated rice, exchangeable Ca, AEZ, maximum temperature ( $T_{\max}$ ), soil type and minimum temperature ( $T_{\min}$ ) were identified as the five most influential variables associated with grain yield. The emergence of Ca as a strong determinant in maize and irrigated rice was most likely associated with soil type and clay mineralogy. Exchangeable bases are a function of soil clay (amount and type) and SOM.

**Table 4** Mean estimates of maize yield responses (in  $\text{Mg ha}^{-1}$ ) to N, P and K, and agronomic efficiencies ( $\text{kg increase in grain kg}^{-1}$ ) as influenced by differences in N, P, and K application ratios. Values in the same column followed by a different superscript are significantly different at  $P < 0.05$ .

N:P:K ratio	N yield response	Agronomic efficiency N	P yield response	Agronomic efficiency P	K yield response	Agronomic efficiency K
1: 0.18: 0.35	2.3 <sup>a</sup>	19.2 <sup>a</sup>	1.59 <sup>a</sup>	72.7 <sup>a</sup>	0.1 <sup>a</sup>	2.45 <sup>a</sup>
1: 0.27: 0.27	2.12 <sup>a</sup>	20.2 <sup>ab</sup>	1.31 <sup>abc</sup>	43.7 <sup>b</sup>	0.75 <sup>bc</sup>	25.16 <sup>b</sup>
1: 0.27: 0.40	2.8 <sup>b</sup>	18.6 <sup>ab</sup>	1.35 <sup>ab</sup>	33.8 <sup>bc</sup>	0.78 <sup>b</sup>	12.99 <sup>c</sup>
1: 0.30: 0.60	1.1 <sup>c</sup>	11 <sup>c</sup>	0.41 <sup>d</sup>	13.7 <sup>d</sup>	0.23 <sup>a</sup>	3.78 <sup>a</sup>
1: 0.33: 0.33	2.5 <sup>ab</sup>	21 <sup>a</sup>	0.8 <sup>cd</sup>	21.2 <sup>cd</sup>	0.12 <sup>a</sup>	3.48 <sup>a</sup>
1: 0.36: 0.36	2.34 <sup>a</sup>	16.7 <sup>b</sup>	1.61 <sup>a</sup>	32.3 <sup>bc</sup>	0.1 <sup>a</sup>	1.98 <sup>a</sup>
1: 1: 1	1.24 <sup>c</sup>	12.5 <sup>c</sup>	0.94 <sup>bcd</sup>	9.49 <sup>d</sup>	0.31 <sup>ac</sup>	3.12 <sup>a</sup>

**Table 5** The top six influential variables identified out of 22 and 25 variables used in random forests algorithm for maize and irrigated lowland (IL), rainfed lowland, and rainfed upland (RU) rice cropping

systems (complete details are provided in Supplementary Figs. S3-S4). For a complete set of variable importance plots, refer to Supplementary Figs. S3 and S4 for maize and rice, respectively.

Crop-system	Response variable	Influential var					
		1st	2nd	3rd	4th	5th	6th
Maize	Grain yield	Ca	pH	Mg	Soil type	K	Mg:K
	N response	Soil type	Mg	Ca	K	Ca:K	Mg:K
	P response	P	Ca	Mg	Clay	pH	Mg:K
	K response	Mg	K	pH	Ca	Mg:K	Soil type
Rice-IL	Grain yield	Ca	AEZ	Tmax	Soil type	Tmin	SSI
	N response	Rainfall	Ca:K	Soil type	Tmax	Tmin	Na
	P response	Sand	Mg:K	Soil type	pH	Ca:K	Total N
	K response	Soil type	Tmax	Na	Rainfall	P	SOC
Rice-RL	Grain yield	Rainfall	Tmin	Tmax	Soil type	Sand	Radiation
	N response	Tmin	Rainfall	Tmax	Ca:Mg	Sand	Soil type
	P response	Soil type	Tmin	AEZ	Rainfall	K rate	SSI
	K response	P	Rainfall	AEZ	Tmin	Na	SSI
Rice-RU	Grain yield	Tmax	Rainfall	Radiation	Variety	Mg:K	Ca:Mg
	N response	Ca:Mg	Tmax	Mg:K	Radiation	Variety	K
	P response	Tmax	K	SSI	Clay	Mg:K	Mg
	K response	K	Radiation	Variety	Ca:Mg	Ca:K	P

In rainfed lowland rice, total rainfall, Tmin, Tmax, soil type and sand content were the most influential variables associated with grain yield. In rainfed upland rice, grain yield was influenced primarily by Tmax followed by total rainfall, solar radiation, variety, Mg:K and Ca:Mg ratios (Table 5). Yield response to N was influenced primarily by Ca:Mg followed by Tmax, Mg:K, solar radiation, variety and exchangeable K, whereas yield response to P was influenced by Tmax, exchangeable K, SSI, clay content, Mg:K and exchangeable Mg (Table 5). On the other hand, yield response to K was influenced primarily by exchangeable K, followed by solar radiation, variety, Ca:Mg, Ca:K and available P (Table 5). As expected, medium and late maturing varieties outperformed early maturing varieties in the rainfed upland rice. This is probably because medium and late-maturing varieties did not face drought at crucial phenology stages. The more extended growth period for medium and late varieties also supported more interception of photosynthetically active radiation resulting in more energy accumulation and conversion to grain.

The emergence of P, K, Ca, Mg, Ca:K and Mg:K as influential variables (Table 5) in maize and rice cropping systems emphasizes the need to prioritize the most valuable soil parameters in predicting yields and yield responses. The Ca:K and Mg:K ratios in soils are essential for the balanced uptake of mineral nutrients by plants because excess concentrations of one can negatively influence plant growth. For example, there is growing evidence of K deficiency in Africa, even in soils

with optimum amounts of exchangeable K (Laekemariam et al. 2018). This is associated with induced deficiencies due to Ca, Mg, and K imbalances (Laekemariam et al. 2018). The literature also suggests that K-induced Mg deficiency is widespread in agroecosystems (Rietra et al. 2017; Xie et al. 2020). Therefore, improved response to applied nutrients and more efficient utilization can occur only when such interactions are fully understood, and corrective measures are taken. K is of particular interest as it is underappreciated despite its interactions with almost all of the essential macronutrients and micronutrients, and its uptake and utilization are closely related to the availability and uptake of other nutrients (Rietra et al. 2017). The total soil K content is also a poor indicator of plant-available K due to inaccurate sampling and analysis methods. Although most soils may have abundant K, highly weathered soils have limited weatherable K reserves. The fraction of plant-available K in soil solution is 0.1–0.2% of total soil K, and the fraction of exchangeable K is 1–2% (Dhillon et al. 2019). The availability of K also depends on the soil type, clay mineralogy, SOM and pH (Dhillon et al. 2019), while K uptake may depend on the amount of ammonium ( $\text{NH}_4^+$ ), sodium ( $\text{Na}^{2+}$ ), copper and zinc oxides in the soil (Bindraban et al. 2015; Wang et al. 2013). The capacity of some soils to fix added K (Elephant et al. 2019) is underappreciated in SSA. These observations highlight the urgent need for research that furthers our understanding of the site-specific interactions between K and other nutrients, and the K fixation capacity of soil in Africa for better soil fertility management.



#### 4 Limitations of the study and data gaps

Although this work aimed to assess the genotype (G) x environment (E) x management (M) interactions in maize and rice yields, the genotype effects could not be adequately addressed because no single variety of maize or rice was used across a large number of sites. Information was also lacking on the days to maturity and yield potentials of the cultivars used. Therefore, it was not possible to group genotypes into homogeneous categories to perform the desired analysis to reveal the genotype effect. It is necessary to assess G x E x M in specific breeding target domains (Futakuchi et al. 2021) to better understand genetic gains, management gains, and their interaction.

Unlike maize, not many NOTs have tested rice responses to the combined application of NPK with micronutrients, lime or manure. Therefore, we were unable to provide an analysis of such results. The limited number of recent studies (e.g., Awio et al. 2021; Senthilkumar et al. 2021) and reviews (Ibrahim et al. 2021) shows that rice response to macronutrients and micronutrients is context-specific. For example, NPK + other macronutrients and micronutrients enhanced lowland rice yield on *Fluvisols* in Tanzania but not on *Plintosols* in Uganda (Awio et al. 2021). The effect of micronutrients on yield was consistent in irrigated rice but was highly variable in rainfed lowland and upland rice in Tanzania (Senthilkumar et al. 2021). Therefore, there is a need to identify soils and production systems where specific macronutrients and micronutrients are limiting. In future NOT experiments, consistent inclusion of micronutrients and macronutrients other than NPK will be of value to better assess their influence on maize and rice yield responses and nutrient use efficiencies.

In both maize and rice NOTs, 19–43% of the sites did not have complete soil test data (Supplementary Tables S2 and S3). This has limited the use of these variables in the random forests model, especially for maize, where more sites had missing values. Therefore, we recommend standardizing methods and reporting of soil clay and sand content, soil pH, SOC, total N, available N, available P, available K, exchangeable K, Ca and Mg to be a minimum data requirement for NOTs. With advances in soil analysis techniques (e.g., near-infrared spectrometry), many soil properties could be quantified fairly rapidly and cheaply. Therefore, we strongly recommend standardizing soil test data for all NOTs and other related trials.

The omission trials analyzed here did not adequately cover the main soil types. For example, >80% of the data for maize response to NPK came from just six soil types: Lixisols, Acrisols, Leptosols, Arenosols, Plinthosols and Vertisols, while Ferralsols, one of the dominant soils of SSA, where maize is cultivated, has not been covered. As in maize, ~80% of the NPK yields of rice came from just six soil types: Luvisols, Arenosols, Alisols, Gleysols, Cambisols and

Ferralsols. Data gaps exist for most soil types where rice and maize can be potentially cultivated. In agroecological zones, subhumid and semi-arid zones represented over 70% of the maize and rice yield data using NPK. The review also revealed regional imbalances in the representativeness of NOTs. For example, maize NOTs were available only from six countries, but over 80% of the NPK yield data came from Nigeria (33%), Tanzania (22%), Malawi (21%), and Ethiopia (12%). In this situation, the main maize growing areas are not adequately represented. The rice NOTs came from 16 countries covering the main rice-growing areas. Although the data adequately covered the major lowland rice production systems, the rainfed upland system was not. We strongly recommend inter-institutional collaboration to develop a standard framework for guiding the selection of trial sites to adequately represent soil types, breeding domains, agroecological zones and socio-economic factors at the regional level. Further effort is needed to reduce the cost of implementation of NOTs, standardizing sampling frameworks and the design of the trials.

The random forest modeling results motivate further studies on interactions between the applied and indigenous soil nutrients as well as farmer management practices and history of input use which affect crop response (Adolwa et al. 2019). More in-depth information on farmer management and water regimes is also required to better understand crop nutrient response patterns.

#### 5 Conclusions

Yields of 4 t ha<sup>-1</sup> in maize and rice were achievable with balanced fertilization. This implies that it is possible to double maize and rice yield with improved nutrient management, even without changes in the varieties used. The balanced application of NPK with other macronutrients and micronutrients reduces spatial variability in maize production systems. It was also revealed that response to K was lower in maize than rice cropping systems. There is a profound variability in maize and rice yield response to K fertilizer, which is driven by the soil available K status and the interactions between applied K and base cations in the soil. The reliability of available K as an indicator of K requirements is often limited by inaccurate sampling and analysis methods. Our analysis also showed that the effect of the other macronutrients and micronutrients on the agronomic efficiency of K is context-specific, highlighting the need for targeted K recommendations. We recommend further research and diagnostic trials to address site-specific interactions between soil nutrients to avoid imbalances and induced deficiencies. These results have important implications for governments, farmers and private sector fertilizer and seed producers in SSA. To optimize returns to investment in fertilizer in maize and rice production systems, there is a need to tailor specific fertilizer formulations

to specific growing conditions. This is particularly relevant for areas with strong yield responses to K, other macronutrients and micronutrients.

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**Data availability** The datasets analyzed for the current study are available from the corresponding author on reasonable request.

**Code availability** Not applicable.

## Declarations

**Conflict of interest** The authors declare no competing interests.

**Ethics approval** Not applicable.

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