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Adapting the QUEFTS model to predict attainable yields when training data are characterized by imperfect management

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ABSTRACT

Understanding yield responses to nutrient application is a key input for extension advice and strategic agricultural investments in developing countries. A commonly used model for yield responses to nutrient inputs in tropical smallholder farming systems is QUEFTS (QUantitative Evaluation of the Fertility of Tropical Soils). While QUEFTS has a strong conceptual foundation, a key assumption is that nutrients are the only limiting factors. One implication of this is the required assumption of 'perfect management'. This may be problematic in the application of QUEFTS in smallholder farming systems with a wide variety of yield limiting factors.

In a previous study, QUEFTS was calibrated using farm trials in two major maize production zones in Nigeria. To reduce observed variability in correlations between estimated soil nutrient (N, P, K) supply and soil parameters (*e.g.* soil organic carbon, soil pH; step 1 of QUEFTS) a Mahalanobis distance method was used to remove data points not adhering to expected correlations. In this study, we assessed an alternative approach: can the QUEFTS model be adapted to fit smallholder farming systems and associated variation in management? Using 676 observations from the same nutrient omission trials in two major maize production zones in Nigeria, we compare a standard linear regression approach with a quantile regression approach to calibrate QUEFTS.

We find that under the standard linear regression approach, there is a poor relation between predicted and observed yields. Using quantile regression, however, QUEFTS performed better at predicting attainable yields – defined as the 90th percentile of observed yields – under a wide variety of production conditions. Our results indicate that using quantile regression as a way to predict attainable yields, is a useful alternative implementation of QUEFTS in smallholder farming systems with high variability in management and other characteristics.

1. Introduction

With cereal yield levels around 1 t ha^{-1}, crop productivity in sub-Saharan Africa (SSA) is low in comparison with other regions (Ehui and Pender, 2005; FAO, 2019). Current yields are only 15–27 % of the water-limited potential yield (van Ittersum et al., 2016), which is the achievable yield when water supply is the only limiting factor (Van Ittersum et al., 2013). Given the anticipated increase in population growth and food demand, significant improvements in SSA's productivity are required (van Ittersum et al., 2016). There is consensus that increased use of inorganic fertiliser inputs will be required for such productivity gains (World Bank, 2005; Holden, 2018; Sanchez, 2002; ten Berge et al., 2019; Wanzala-Mlobela et al., 2013), as current fertiliser use levels in SSA are low (Banful et al., 2010; Jayne and Rashid, 2013; Morris et al., 2007; Sheahan and Barrett, 2014) with 16.2 kg fertiliser per ha in 2016 (World Bank, 2019).

Despite this consensus, increased fertiliser application does not always translate into increased yields. Responses to fertiliser application vary considerably in practice. In a meta-analysis on the agronomic nitrogen use efficiency (N-AE) of inorganic fertiliser across SSA, the

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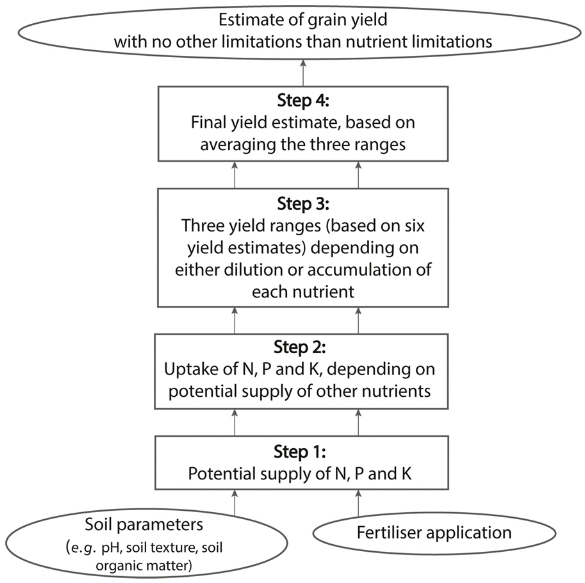

Fig. 1. Flow diagram of the four steps followed in the QUEFTS model to estimate crop yields based on soil parameters and fertiliser application.

average N-AE for maize was found to be 18 kg additional grain yield per kg N applied (in dry weight; Ichami et al., 2019). Variation from this average value is large with observed N-AE values in the field ranging from negative up to 50 kg grain kg N^{-1} (ten Berge et al., 2019; Vanlauwe et al., 2011).

The variable responses to fertiliser application in SSA are often attributed to different levels of inherent soil fertility and management (Njoroge et al., 2019, 2017; Ojiem et al., 2014; Vanlauwe et al., 2011; Zingore et al., 2007). For example, soils that are very low in organic matter content show a lower fertiliser response than soils with a higher organic matter content (Marenya and Barrett, 2009; Tittonell and Giller, 2013; Zingore et al., 2007). Other soil parameters found to correlate with fertiliser response are soil pH (Burke et al., 2017; Ichami et al., 2019), soil texture (Burke et al., 2017), exchangeable K and P-Olsen (Ichami et al., 2019).

Site-specific fertiliser recommendations have been proposed to account for the variation in yield responses by optimizing fertiliser use based on specific soil conditions (Dobermann et al., 2002). One manner to provide such site-specific fertiliser recommendations is using fertiliser response models such as QUEFTS (QUantative Evaluation of the Fertility of Tropical Soils). The QUEFTS model predicts yield based on soil parameters and fertiliser inputs (Janssen et al., 1990; Smaling and Janssen, 1993). In QUEFTS, a number of equations link soil parameters to soil nutrient (N, P, K) supply, fertiliser recovery, nutrient uptake and grain yields (Fig. 1). In step 1, soil parameters (soil organic matter, pH, percentage clay, P-Olsen and K_{exch}) are linked to potential soil supply of N, P and K (Janssen et al., 1990; Smaling and Janssen, 1993). In steps 2–4, nutrient uptake and yield are estimated based on the calculated soil supply of N, P and K in step 1 and fertiliser application.

The strength of QUEFTS lies in the manner in which it treats the response of the three macronutrients N, P and K: separately vis-à-vis their interactions. This enables the identification of locally optimal combinations of N, P and K fertiliser application rates. The QUEFTS model has gained widespread use within the scientific and agricultural community, mainly due to the limited amount of required input data (*i.e.,* soil properties, fertiliser application rate and potential yield) and relative ease of use. With new geospatial data tools and larger access to open data, there is an increased demand for fertiliser response maps, based on models such as QUEFTS.

The weakness of QUEFTS also lies within its design: QUEFTS predicts yields based on soil conditions and fertiliser application, under the condition that there are no other yield limiting factors (such as late planting, seed quality issues, occurrence of weeds, pests and diseases or issues such as soil compaction). In practice, especially in tropical smallholder farming systems, these limitations are widespread, even in researcher-managed or on-farm field trials. In Shehu et al. (2019), such yield data, limited by other factors than nutrients, was used to calibrate QUEFTS. To accommodate calibration, an outlier selection was performed based on expected correlations between soil characteristics and soil nutrient supply. We see two limitations of this approach: 1) Data point removal is based on hypothesized correlations (correlations which are then used in QUEFTS); and 2) variation in yield responses that smallholder farmers experience might be reduced.

To circumvent these two limitations, in this study we recalibrated and validated QUEFTS using the same TAMASA nutrient omission trial (NOT) dataset for Nigeria while basing the outlier selection only on observed extremities in plant parameters and compared results with the Shehu et al. (2019) calibration. In addition, we used a quantile regression as an alternative approach to calibrate QUEFTS and predict attainable yields.

2. Materials and methods

2.1. The QUEFTS model: four steps

The following sections concisely describe the QUEFTS model (Fig. 1), for a more elaborate explanation readers are referred to Janssen et al. (1990) and Smaling and Janssen (1993).

2.1.1. QUEFTS step 1

In the first step of the QUEFTS model, soil nutrient supply of nitrogen (N), phosphorus (P) and potassium (K) is calculated using four soil parameters: pH, soil OC, P-Olsen, and exchangeable K. Additional to the nutrient supply from the soil, nutrient supply from fertiliser application is calculated by adding a term that calculates the fertiliser recovery of applied fertilisers. Based on a number of trials in Kenya and Suriname, Janssen et al. (1990) developed Eqs. 1–6.

$$S_N = fN * 6.8 * orgC + I_N * R_N \tag{1}$$

$$S_p = 0.5 * P\text{-}Olsen + fP * 0.35 * orgC + I_P * R_P \tag{2}$$

$$S_K = \frac{(fK * 400 * K_{exch})}{(2 + 0.9 * orgC)} + I_K * R_K \tag{3}$$

$$fN = 0.25 * (pH - 3) \tag{4}$$

$$fP = 1 - 0.5 * (pH - 6)^2 \tag{5}$$

$$fK = 0.625 * (3.4 - 0.4 * pH) \tag{6}$$

Where S_N, S_P and S_K, are the soil nutrient supply of N, P and K in kg ha^{-1}; *fN*, *fP*, *fK*, are the pH correction factors of N, P and K supply, respectively (-); I_N, I_P, I_K, are the nutrient inputs of N, P and K in terms of fertiliser application in kg ha^{-1}; R_N, R_P, R_K, are the maximum recovery fractions for fertiliser N, P and K (-); *orgC* is soil OC in g kg^{-1}; *P-Olsen* is soil P-Olsen in mg kg^{-1}; K_{Exch} is soil exchangeable K in mmol kg^{-1}; *pH* is soil pH.

Eqs. 1–3 are used to calculate the soil nutrient supply and Eqs. 4–6 express the pH correction factors for Eqs. 1–3, respectively. The equations calibrated by Janssen et al. (1990) apply to soils with a pH from 4.5 to 7 and a maximum soil OC, P-Olsen and exchangeable K below 70 g kg^{-1}, 30 mg kg^{-1} and 30 mmol kg $^{-1}$, respectively.

Smaling and Janssen (1993) recalibrated QUEFTS using different parameters in the equations for nutrient supply prediction. N supply was predicted based on the organic soil N, temperature and clay percentage. P supply was predicted based on total P, soil OC and pH. K supply was

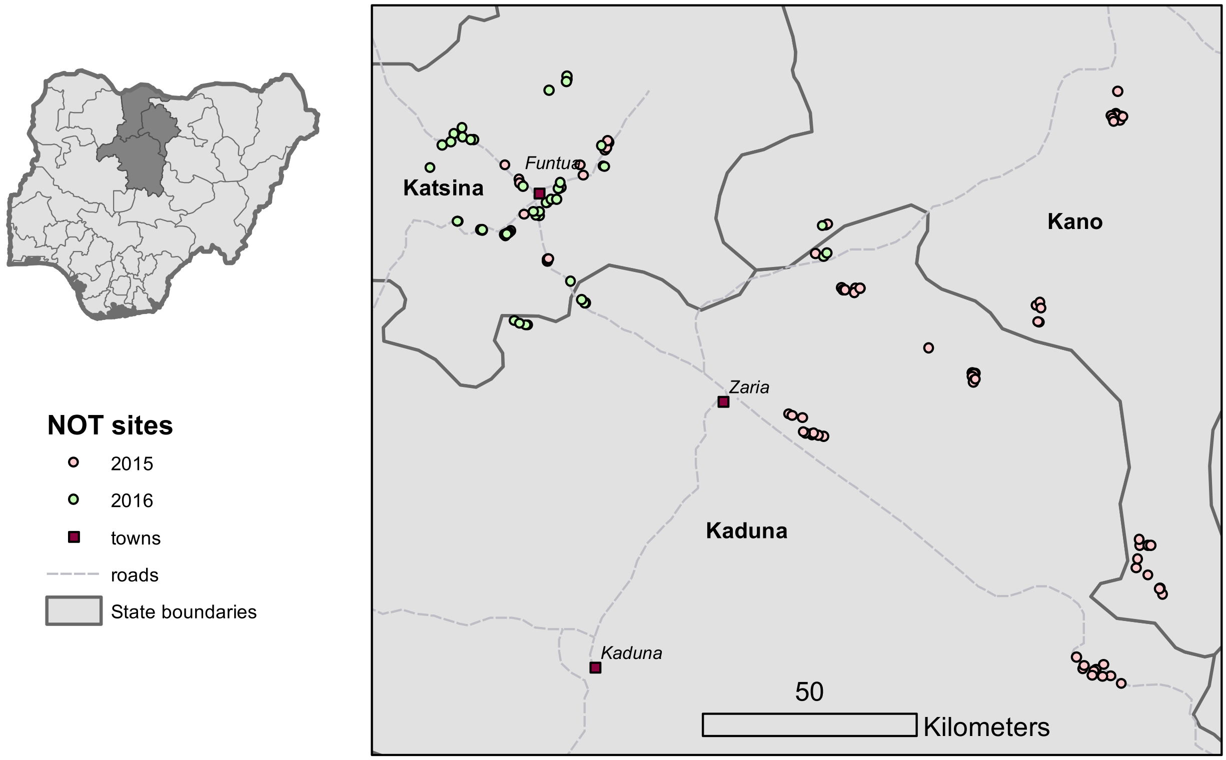

Fig. 2. Map of Nigeria indicating experimental sites. Fields were located in two different agro-ecological zones (AEZ's).

predicted based on exchangeable K and soil OC.

2.1.2. QUEFTS step 2

Step 2 of QUEFTS quantifies the relation between potential soil nutrient supply and actual N, P and K uptake. QUEFTS assumes that the uptake of one nutrient is limited by the uptake of another nutrient. In the case of N, N uptake is limited by P uptake and by K uptake. This results in two N uptake estimates, namely one for the nutrient combination NP and one for the nutrient combination NK. In confirmation with the law of the minimum, QUEFTS takes the lowest of the two N uptake estimates for further calculations. P and K uptake are calculated in the same way (Janssen et al., 1990).

For the calculation of nutrient uptake, three defining curves can be described on the relation between the potential supply of a given nutrient and the actual uptake of the given nutrient (I,II and III). Here we explain these for N, but it equally applies to P and K. In curve I, potential N supply is relatively low compared to potential supply of P or K. As a result, N will be diluted to the maximum in the crop. In this situation, potential N supply is assumed to be equal to the actual N uptake ($U_N = S_N$; Sattari et al., 2014). In curve III potential N supply is relatively high compared to the potential supply of P or K. N uptake will be limited by the amount of P or K taken up ($U_P = S_P$; $U_K = S_K$). In this situation, N will be accumulated to the maximum. Curve II is an integration of a regression between the extremes of curves I and III.

2.1.3. QUEFTS step 3

In step 3 of QUEFTS, nutrient uptake is converted into maize yield. For each nutrient (N,P,K) a yield estimate is calculated for maximum accumulation and dilution of that nutrient within the crop. This results in 6 yield estimates. It is important that the yield range of a certain nutrient combination does not exceed the maximum yield given the uptake of the third nutrient and that the estimated yield remains lower than the potential yield for a given site. The potential yield should thus be estimated prior to running the QUEFTS model. For this study we assumed a potential yield of 10 t ha^{-1}, based on mean annual precipitation (Shehu et al., 2019). Lastly, the minimum requirement for establishing maize yield is an uptake of 5 kg N ha^{-1}, 0.4 kg P ha^{-1} and 2 kg K ha^{-1}, as lower uptake of nutrients will not result in any yield. The boundary lines for a minimum and maximum yield for a given nutrient uptake estimated in this step are crop dependent (Antwi et al., 2017; Janssen et al., 1990; Setiyono et al., 2010; Shehu et al., 2019; Smaling and Janssen, 1993).

2.1.4. QUEFTS step 4

In step 4 of QUEFTS, the final step, one yield estimate is predicted by averaging the 6 yield estimates calculated in step 3 (section 2.1.3).

2.2. Data collection

2.2.1. Study area

Our study area covers the main maize producing areas of northern Nigeria – Kano, Kaduna and Katsina states – which together are characterized by two agroecological zones (AEZs), the Sudan Savanna (SS) and the Northern Guinea Savanna (NGS) (Fig. 2). SS has a drier climate and received 600–800 mm of rain annually in 2015 and 2016. Precipitation in NGS was 900–1500 mm annually in 2015 and 2016. In both AEZs the rainy season lasts from May to September. May and October are the hottest months with a maximum temperature between 35 and 40 °C and a minimum temperature between 20 and 25 °C. January and August are the coldest months with a maximum temperature around 30–35 °C and a minimum temperature around 15 °C. Soils in the area are haplic Acrisols, haplic Luvisols and haplic Vertisols (ISRIC, 2018). For a more detailed description of the study area the reader is referred to Shehu et al. (2018).

The data set for this study was obtained from NOTs conducted in 95 and 103 fields in the 2015 and 2016 rainy seasons, respectively (Fig. 2). In 2015 the fields were located in 10 different districts, while in 2016 fields were spread over 14 different districts. The sampling frame was designed to be representative of the variation in soils and other biophysical production characteristics across the area of interest, including soils and agroecological variation.

2.2.2. Experimental design

In each field, NOTs were installed with six different treatments. The treatments included a control treatment where no nutrients were applied to the soil, treatments where PK, NK and NP were applied and thus respectively N, P and K were omitted, a NPK treatment with all nutrients applied and a NPK + micronutrients treatment where NPK and micronutrients (S, Ca, Mg, Zn & B) were added to the soil. Yield data from the NPK + micronutrients treatment was not used in this study. In NGS, N was applied at a rate of 140 kg ha^{-1} applied in three equal split applications at planting, 21 and 42 days after emergence. In SS, N was applied in three equal split applications at a rate of 120 kg ha^{-1}. P and K were applied at planting at a rate of 50 kg ha^{-1} in NGS and 40 kg ha^{-1} in SS. Fertiliser treatments were sufficient to reach a potential maize yield of 10 t ha^{-1} in NGS and 8 t ha^{-1} in SS.

Plots in the research-managed trial sites had a size of 5 * 6 m and were prepared by mechanical tillage before planting. Planting was done with a spacing of 0.75 m in the inter-row and 0.25 m in the row resulting in a plant density of 53,333 plants ha^{-1} after thinning. Manual weeding was done at least twice during the season. At each location an open pollinated maize (OPV) variety and a hybrid variety were planted, resulting in 12 treatments in total at each trial site. The OPV variety used in NGS and SS matures in 105–110 days and 90–95 days respectively. For hybrids the same variety was used in NGS and SS but differed for 2015 and 2016. The variety used in 2015 matures in 105–110 days and the variety used in 2016 matures in 105–118 days.

2.2.3. Soil data collection

In every site four soil samples were taken from the 0−20 cm upper soil layer before fertilisers were applied. Soil samples were taken in a zig-zag pattern and thoroughly mixed to create one mixed soil sample and thus one soil measurement per farm. Soil analyses were carried out in the International Institute of Tropical Agriculture (IITA) lab in Nigeria. Soil organic carbon was measured with a modified Walkley and Black method (Heanes, 1984). Total nitrogen was assessed with the micro-Kjeldahl digestion method (Bremner, 1996) and the concentration was measured colorimetrically using N-autoanalyzer (Technicon autoanalyzer II, SEAL Analytical Inc, Mequon, WI, USA). Available phosphorus, available sulphur, exchangeable cations (K, Ca, Mg, and Na) and micronutrients (Zn, Fe, Cu, Mn and B) were assessed with the Mehlich-3 extraction procedure (Mehlich, 1984). A glass electrode pH meter was used to measure soil pH in a soil: water ratio of 1:1. The method by Gee and Or (2002) was used to assess the particle size distribution. For descriptive statistics of soil parameters readers are referred to (Shehu et al., 2018, 2019).

2.2.4. Agronomic data collection

From each 5 * 6 m plot, the middle 3 * 3 m maize was harvested at physiological maturity for crop cut measurements. Plant density, cob count, total cob weight and stover fresh weight were recorded. Shelling percentage and grain moisture content were measured from a smaller set of randomly selected cobs (5 in 2015 and 10 in 2016) to calculate dry grain weight from the total fresh cob weight. Grain yield was expressed in 15 % moisture content. From the stover, five stalks were randomly selected and oven-dried to constant weight at 60 °C to measure moisture content. In 2015, this procedure did not go as planned. From the correctly measured stalks an average moisture content of 52 % was used to convert stover weight into dry weight. The dried grain and stover samples were also used to assess N, P and K content in the grain and stalks. Nitrogen (N) content was digested using micro-Kjeldahl digestion method (Bremner, 1996) and the concentration determined colorimetrically using autoanalyzer (Technicon autoanalyzer II, SEAL Analytical Inc, Mequon, WI, USA). P and K concentrations were measured with inductively coupled plasma optical emission spectroscopy (ICP-OES, Optima 80, Winlab 5.5, PerkinElmer Inc., Waltham, MA, USA) after digestion with nitric acid (HNO_3).

2.2.5. Outlier selection in Shehu et al (2019)

The total Nigeria TAMASA NOT data set contained 1825 observations. Of these, 455 observations contained missing values in at least one of the measured parameters and were omitted from analysis in the previous study by Shehu et al. (2019) as well as in our study.

Following, in Shehu et al. (2019) a Mahalanobis Distance outlier selection was performed on the whole dataset to discard multivariate outliers ($n = 219$) and separately again for the calibration of each supply function for N, P and K ($n = 216$). Hence, in total 434 data points out of 1370 observations were removed from the analysis in Shehu et al. (2019). A Mahalanobis Distance outlier selection can be used to filter out unusual combinations of variables. Such a combination could for instance be a field with a high amount of available P in the soil and a very low yield. However, QUEFTS also uses available P as one of the variables used to predict yield. In this case, the outlier selection influences the equation that is to be calibrated or parameterized. Moreover, the observed variation in expected correlations between soil characteristics and nutrient supply might have valid reasons, such as heterogeneity in management of the farmers' fields.

2.2.6. Outlier selection based on plant parameters

As an alternative approach, in our study, outliers were only removed based on extremities observed in plant parameters that could potentially influence observed relations strongly. Plant parameter observations were removed based on standardized residual values of a linear mixed effects model larger than -4 or 4 ($n = 52$) (an approach similar to Ronner et al. (2016)). For the soil parameters there was no reason to assume any incorrect measurements. In total 1318 observations were left for data analysis.

2.2.7. Other data preparation

For calibration purposes, trial sites were selected where within the same field and for one variety, yield and soil data was available for the four treatments with nutrient application (PK, NK, NP and NPK treatment) ($n = 676$). A total of 169 complete trials (field * variety) were found and included in the calibration exercise. Of these 169 complete trials, 84 were from OPV and 85 from hybrids. Eleven fields were located in SS and 158 fields in NGS. Forty complete trials were from 2015 and 129 from 2016. The other data points were used for validation. Of those 676 osbervations used for calibration, d data from the control plots ($n = 154$) wereere not used for calibration and were excluded from the analysis.

No distinction was made between OPV and hybrid as the varieties responded similarly to nutrient application and had a similar harvest index (Shehu et al., 2018, 2019). Data from the two different years were pooled for analysis. The fields measured in 2016 were different from those measured in 2015 and it was thus not possible to form a panel. In the analysis of soil nutrient supply against soil parameters (step 1 of QUEFTS) no distinction was made for AEZ. The main reason for this was that ideally one model calibration should be made for the whole dataset. A practical reason was that few data points from SS remained after data preparation.

For running QUEFTS with Janssen et al. (1990) parameters, P-Olsen is needed. In this study P-Mehlich was measured. P-Olsen was approximated by dividing P-Mehlich values by three (Onduru and Du Preez, 2007).

2.3. Calibration of QUEFTS: standard linear or quantile regression?

First, soil nutrient supply of N, P and K and recovery of applied N, P and K were estimated for each trial location (Sections 2.3.1 and 2.3.2). Then, two different methods were used to calibrate the first step of

QUEFTS: (1) Nutrient supply was correlated to soil parameters using standard linear regression, a standard procedure to calibrate QUEFTS; and (2) boundary lines of nutrient supply were correlated to soil parameters using quantile regression, as an alternative approach to calibrate QUEFTS (Sections 2.3.3 and 2.3.4). We used quantile regression instead of the upper limits of the prediction intervals resulting from the standard linear regression, because the slopes of the quantile regression lines behaved differently than the slopes of the standard linear regression. Hence, quantile regression resulted in the best regression estimates for the best performing fields.

Based on significant correlations found in the mentioned analyses, two sets of soil supply functions were computed. One set of functions was computed for the calibration with standard linear regression and one set of functions for the calibration using quantile regression. Finally, for both methods Step 2–4 of the QUEFTS model were followed to complete the model calibration (Section 2.3.5).

2.3.1. *Estimating potential soil nutrient supply in a specific location*

For both methods, potential soil nutrient supply was derived from the measured nutrient uptake in the treatment where that specific nutrient was omitted. As such, it was assumed that the potential soil N supply was equal to the measured N uptake by the plants in the PK treatment. Similarly, the supply of P and K were derived from the measured P and K uptake in the NK and NP treatment respectively. Hereby we assumed that the availability of the two applied nutrients was high enough to ensure that the omitted nutrient was limiting and uptake was thus maximal. In the following sections we will use the term apparent nutrient supply to indicate that we used measured nutrient uptake as an estimate of the nutrient supply of the soil.

In some cases, nutrient uptake in the nutrient omitted treatment plot was lower than nutrient uptake in the corresponding control plot. These cases were not excluded from the analysis as this was assumed to be due to random errors. We assume that these random errors exist in all fields. Therefore, removing only the cases where nutrient uptake in the nutrient omitted treatment plot is lower than in the control plot would lead to a positive uptake bias.

2.3.2. *Estimating recovery of applied nutrients in each trial location*

In this study, nutrient recovery of applied fertilisers (N, P or K) was calculated as the difference in nutrient uptake between a plot receiving NPK and a plot where the specific nutrient was omitted, divided by the amount of the given nutrient applied in the NPK treatment (Eq. 7). For example, for N, this means the difference in N uptake between a plot receiving NPK and a plot receiving PK, divided by the amount of N applied. Similarly, P and K recovery of applied fertilisers were calculated from the difference in nutrient uptake between the NPK and NK and NPK and NP treatment, respectively.

$$R_i = \left(U^i_{NPK} - U^i_j\right) \Big/ I_i \tag{7}$$

Where R_i is the recovery fraction of nutrient *i* (N, P or K) (-); $U^i{}_{NPK}$ is the uptake of nutrient *i* in the NPK treatment in kg ha^{-1}; $U^i{}_j$ is the uptake of nutrient *i* in the omission treatment *j* (PK, NK or NP) in kg ha^{-1}; I_i is the nutrient input rate of nutrient *i* in kg ha^{-1}.

2.3.3. *Relating nutrient supply and nutrient recovery to soil parameters using standard linear regression*

First, apparent nutrient supply and recovery fractions of N, P and K were plotted against different soil parameters to visually check and understand the correlations between apparent nutrient supply or recovery and soil parameters. A linear mixed effects model (Eq. 8) was used to test whether relations were significant. Correlations were considered significant at $p < 0.05$. Year and district were added as random variables, whereby districts were nested within years. Analysis was performed with the 'nlme' package in R version 3.4.3.

$$\text{Model}: S_i \sim \mathit{soil\ property}_{ij},\ \text{random} = \sim 1 \mid \mathit{year} / \mathit{district} \tag{8}$$

Where S_i is the apparent nutrient supply, of nutrient *i* in kg ha^{-1}; where *soil property*$_{ij}$ is one or more of the measured soil properties *j* used to estimate the apparent supply of nutrient *i*.

Initially, recovery fractions of N, P and K were related against soil parameters, but no significant relations were found (data not shown). Therefore, only average recovery fractions of N, P and K were computed with a linear mixed effects model. (Eq. 9).

$$\text{Model}: R_i \sim 1,\ \text{random} = \sim 1 \mid \mathit{year} / \mathit{district} \tag{9}$$

2.3.4. *Adapting QUEFTS: relating nutrient supply to soil parameters using quantile regression*

Given the heterogeneity in management of smallholder farmers, chances are high that the assumption of no yield limiting factors other than nutrient limitation was violated in farmers' fields. As an alternative option, a quantile regression was performed to estimate boundary lines of maximum potential soil supply of N, P and K for given levels of soil parameters. The 'quantreg' package in R version 3.4.3 was used to draw boundary lines through the 90th percentile. The quantile regressions were also run for different quantiles to check if slopes changed for different quantiles. For N and K this was not the case. For P there were two points having a large influence on the shape of the curve. These two points were therefore not taken into account in the boundary analysis. ANOVA was used to test significance of the quantile regression lines. Average recovery fractions of N, P and K applied were estimated using standard linear regression.

2.3.5. *QUEFTS step 2 to 4*

For QUEFTS calibration, the relationships between potential nutrient supply and soil parameters in a specific region needs to be quantified (step 1). Step 2 to 4 are mainly plant dependent and often do not need further calibration. Therefore, the parameters as described by Shehu et al. (*2019*) were used for step 2 to 4. The calibration parameters adopted from Shehu at al. (2019) include the boundary lines of physiological or internal efficiency in kg grain kg^{-1} nutrient of 32 and 79 for N, 164 and 528 for P, and 24 and 136 for K. Maximum attainable yield was set at 10 t ha^{-1} for NGS and 8 t ha^{-1} for SS.

2.4. *Validating the different versions of QUEFTS equations*

Validation data ($n = 488$) was taken from all fields where one or more values were missing. This provided sufficient data to validate the recalibrated versions of the QUEFTS model. QUEFTS was run with soil data and yield data using four sets of step 1 equations: (1) the original QUEFTS equations (Janssen et al., 1990); (2) equations previously calibrated on the Nigeria NOT data using standard linear regression (Shehu et al., 2019); (3) equations calibrated on the Nigeria NOT data using standard linear regression in this study; (4) equations calibrated on the Nigeria NOT data using quantile regression. Equation set 2 was found by using a Mahalanobis Distance outlier selection method. Equation sets 3 and 4 were found using an outlier removal based on plant parameters. Following, yield estimates were compared with observed yields for each location.

Models based on standard linear regression (sets 1–3) were compared for best fit with the root mean square error (RMSE, calculated as the square root of the mean squared difference between observed and predicted values). The model based on equation set 4 was considered valid if the predicted boundary yield line was similar to the measured yield for the 0.9 quantile. It was not possible to use any direct measure to compare the models based on sets 1–3 to the model based on set 4 because they are calibrated in different ways.

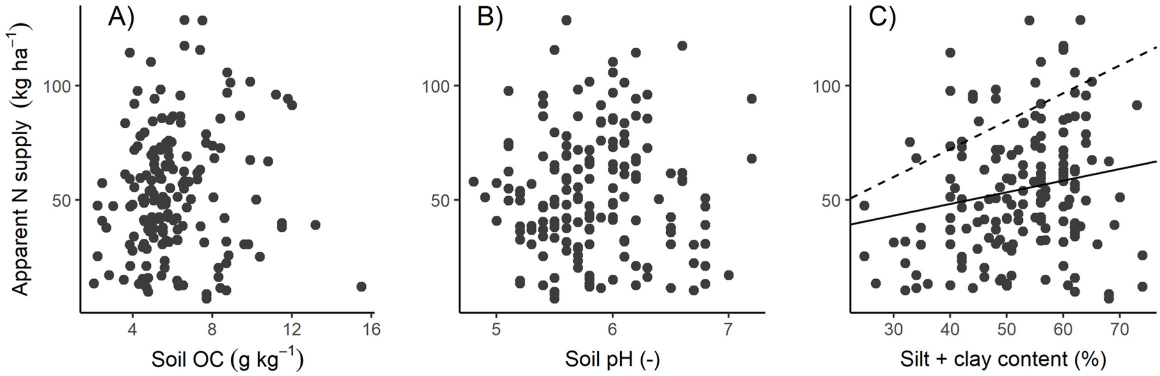

Fig. 3. Apparent N supply (in kg ha^{-1}) in the PK treatments plotted against soil OC (g kg^{-1}) (A) soil pH (B) and silt + clay ilt content (%) (C). The solid line indicates a significant regression line estimated with a linear mixed effects model. The dashed line indicates the boundary line of the 0.9 quantile.

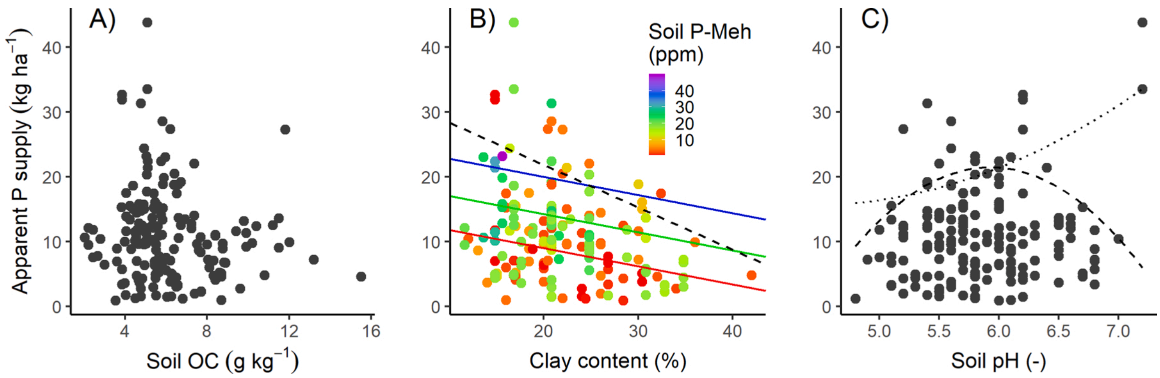

Fig. 4. Apparent P supply (in kg ha^{-1}) in the NK treatment against soil OC (g kg^{-1}) (A), clay content (%) (B) and soil pH (C). in plot B the coloured solid lines indicate significant regression lines for different levels of soil available P (ppm) estimated with a linear mixed effects model and the dashed line indicates the boundary line of the 0.9 quantile. In plot C the dashed line indicates the boundary line for the 0.9 quantile excluding observations in the top right corner, the dotted line indicates the boundary line for the 0.9 quantile including observations in the top right corner.

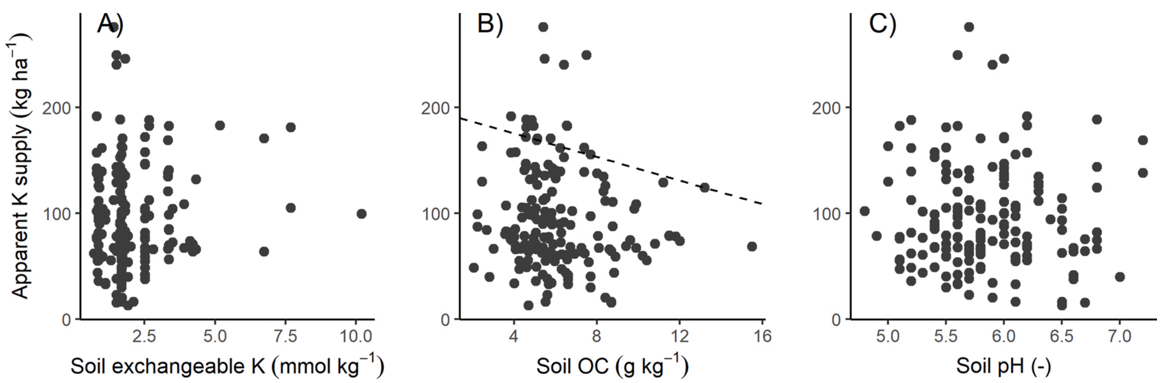

Fig. 5. Apparent K supply (in kg ha^{-1}) in the NP treatment against soil exchangeable K (mmol kg^{-1}) (A), soil OC (g kg^{-1}) (B) and soil pH (C). The dashed line indicates the boundary line of the 0.9 quantile.

2.5. Gaining further insights in causes for observed variation

Observed and predicted boundary lines are indicative of maximum yield, but do not provide insights into observed variation. Therefore, we attempted to explain part of the variation in yield below the observed and predicted boundary line, using supplemental data. In both years, plant density at harvest was measured. It was evaluated whether plant density, as a proxy for suboptimal management, could be used to explain part of the yield variation.

3. Results

3.1. Calibration of QUEFTS step 1 using standard linear regression

3.1.1. Soil nutrient supply

In the original QUEFTS equations, calibrated on field data from Kenya (Janssen et al., 1990), soil N supply is linearly correlated with soil OC and soil pH (Eq. 1). Alternatively, our data analysis showed no significant correlation between either soil OC or soil pH and apparent N supply (Fig. 3A and B). In our study, there was a significant correlation between silt + clay content and apparent N supply (slope = 0.55, p =

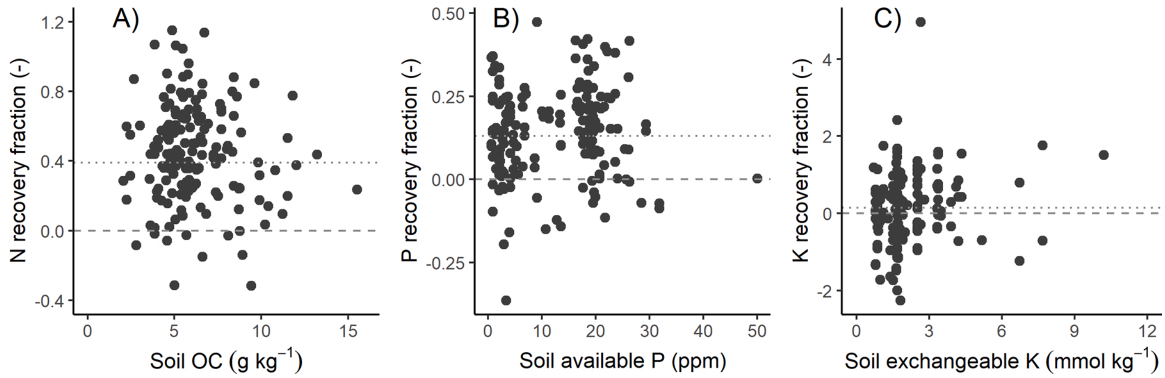

Fig. 6. Recovery fraction of N (A), P (B) and K (C) against soil OC (g kg^{-1}), soil available P (ppm) and soil exchangeable K (mmol kg^{-1}) respectively. The horizontal dashed lines indicate the border lines between a positive and negative recovery. The dotted lines indicate the average recovery fractions.

0.02). The range in apparent N supply was however very large (Fig. 3C).

For soil P supply, the original QUEFTS equations assume a linear correlation between soil P supply and soil OC and P-Olsen. Additionally, a pH correction factor with a parabolic optimum around a pH of 6 is used in the original QUEFTS equations to predict soil P supply. In this study, no correlation was observed between soil OC and apparent soil P supply (Fig. 4A). Based on our field data, a significant correlation was found between soil available P and apparent soil P supply, being dependent on the clay content of a soil ($U_P \sim$ *clay content* + *soil P-Meh*, random = 1 | *year / district;* Fig. 4B).

Based on our field data, no significant correlations were found between apparent soil K supply and soil OC, soil pH or soil exchangeable K which are all considered in the original QUEFTS model (Fig. 5). For additional figures on apparent nutrient supply and soil parameters, readers are referred to appendix A.

3.1.2. Fertilizer recovery

The average recovery fractions for N, P and K were 0.39, 0.13 and 0.14 (Fig. 6). The lowest observed N recovery was - 0.3 and the highest N recovery was 1.2. Except for some outliers, P recovery ranged from - 0.2 to 0.4 and the range for K recovery was from -2 to 2. Variation in nutrient recovery was clearly present. No significant correlations were observed between soil parameters (soil OC, soil texture, soil pH, soil N, soil P and soil exchangeable K) and nutrient recovery (data not shown).

3.1.3. QUEFTS step 1 equations based on standard linear regression

Based on significant correlations between apparent nutrient supply and soil properties with the mixed effects models, nutrient supply prediction equations were developed (Eqs. 10–12). Since for K no significant correlations were found, the average measured apparent K supply was used. A nutrient recovery term was added to all the three equations according to the QUEFTS model principle as earlier described, based on the average nutrient recovery fraction.

$$S_N = 24.2 + 0.55^*(clay + silt\ content)\ +\ I_N^*\ 0.39 \tag{10}$$

$$S_p = 14.1 - 0.28^*clay\ content + 0.23^*P\text{-}Meh\ +\ I_P^*0.13 \tag{11}$$

$$S_K = 90.1\ +\ I_K^*0.14 \tag{12}$$

3.2. Calibration of QUEFTS step 1 using quantile regression

3.2.1. Soil nutrient supply

The boundary analysis for the 0.9 quantile showed that maximum apparent N supply increased with silt + clay content (y = 0.72 x + 51.9; Fig. 3C).

When the quantile regression was performed for all data on apparent P supply and soil pH, a parabolic boundary line was found with a minimum apparent P supply with a pH less than 5 and a maximum around a pH of 7 (Fig. 4C). This relation was however counterintuitive and dependent on two outliers (Fig. 4C; two observations in the top right corner). When these two outliers were excluded, a quadratic boundary line was found with an optimum around a pH of 6 (y = -9.57 x^2 + 113.4 x – 314.7). Therefore, this equation was used in the boundary model of QUEFTS. Additionally, quantile regression for the 0.9 quantile showed that maximum apparent P supply decreased with an increasing soil clay content (Fig. 4B) (-0.65 * clay content + 34.89). For the estimation of

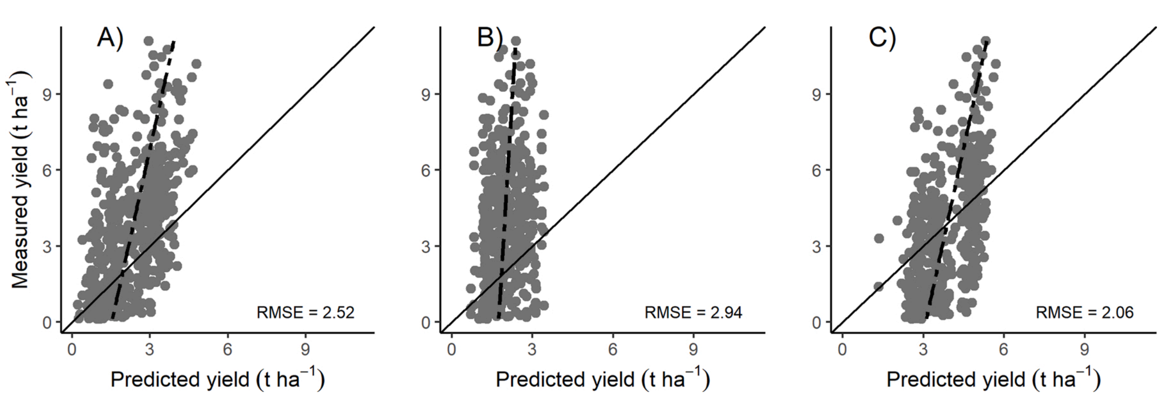

Fig. 7. Measured yield against predicted yield (t ha^{-1}) for the original QUEFTS model (A), the model calibrated by Shehu et al. (2019) (B) and the adapted model in this study (C). The solid black lines indicate the 1:1 line. The dot dashed lines indicate the regression lines.

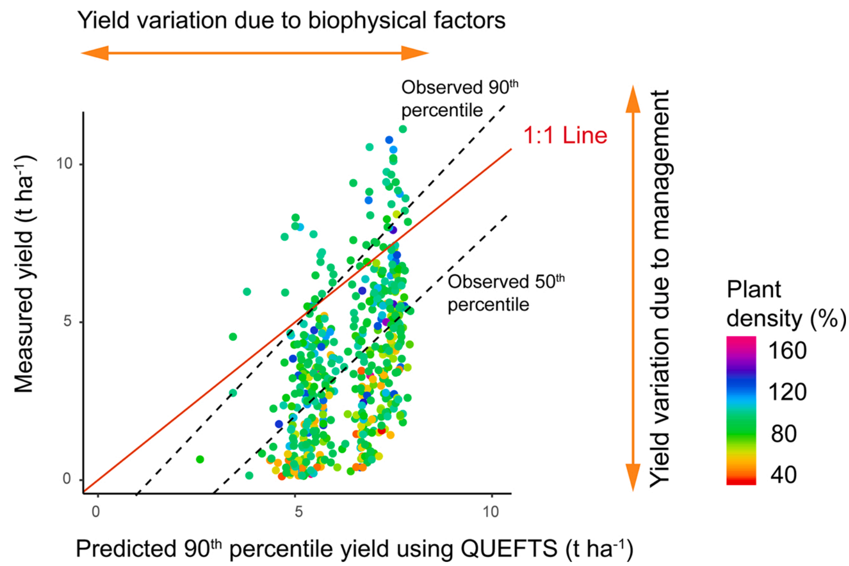

Fig. 8. Measured yield (in t ha^{-1}) against predicted yield (in t ha^{-1}) using the boundary line equations. Different colours of the dots indicate different plant density levels at harvest. 100 % refers to 53 333 plants ha^{-1}. The solid red line indicates the 1:1 line. The dashed lines indicate the boundary lines following the 90th and 50th percentile.

apparent P supply, it was assumed that the lowest values of the two equations was equal to the maximum apparent P supply.

Quantile regression showed that the maximum apparent K supply decreased with increasing soil OC (y = -5.5 x + 197), which is in line with the original QUEFTS assumption that K supply decreases with diminishing soil OC (Fig. 5B).

3.2.2. *Fertilizer recovery*

No correlations were found between soil properties and maximum nutrient recovery using quantile regressions as was the case using method 1. Therefore, in method 2 a similar constant average fertiliser recovery rate was assumed regardless of soil properties.

3.2.3. *QUEFTS step 1 equations using quantile regression*

Based on the boundary lines, boundary equations were formulated that predicted maximum apparent nutrient supply (Eqs. 13–15). Similar to the standard linear regression equations a nutrient recovery term was added based on the average nutrient recovery fraction.

$$S_N = 51.9 + 0.72*(clay + silt\ content) + I_N*0.39 \tag{13}$$

$$S_p = \min\left(-314.7 - 9.57*soil\ pH^2 + 113.4*soil\ pH,\ 34.9 - 0.65*clay\ content\right) + I_P*0.13 \tag{14}$$

$$S_K = 197.4 - 5.50*soil\ OC + I_K*0.14 \tag{15}$$

3.3. *Validation of the different sets of QUEFTS equations*

3.3.1. *Validity of QUEFTS step 1 equations using standard linear regression*

None of the QUEFTS models in which step 1 was calibrated using standard linear regression showed good correlations between predicted and observed yields when validated with an independent data set (Fig. 7A,B,C). Between them, the newly found equations predicted yields relatively better, followed by the original QUEFTS equations and the version from Shehu et al. (2019) performed worst, albeit with small differences among them (RMSE 2.06, 2.52 and 2.94 respectively). In all three cases the regression line deviated substantially from the 1:1 line.

3.3.2. *Validity of QUEFTS step 1 equations using quantile regression*

The QUEFTS boundary model predicts the boundary or attainable yield (90th percentile), shown as the red 1:1 line in Fig. 8. The observed 90th percentile yield line (upper dotted line, Fig. 8) was very similar to the predicted 90th percentile yield. This shows that the boundary line model was able to predict maximum yield accurately. The 50th percentile showed that the median yield for farmers is more or less three tonnes per hectare less than the attainable yield, indicating a large range in yield responses under similar soil conditions where the measured biophysical soil factors alone were not able to explain yield variation. With biophysical factors, we specifically refer to the variables either tested for or included in the calibrated QUEFTS model (*i.e.*, soil carbon, clay and silt content, soil pH, soil available P and soil exchangeable K) and potential water limited crop yields (which are dependent on climate).

Considering the range of relevant biophysical factors included and the in-field observations on variations in management, we thus observe two types of variation in the analysis of yield responses: (1) variation on the x-axis which is defined by biophysical factors and (2) variation on the y-axis which is determined by farmer management (Fig. 8). Using plant density as an explanatory factor showed that most fields with plant densities lower than 60 % had yields below the 50th percentile. Although plant density is only a single parameter on management, we derive that management related factors played a large role in the observed variation in yield response to fertiliser application and soil characteristics. For the relation between yield and plant density at harvest readers are referred to Appendix C.

4. Discussion

4.1. *Main findings*

Our study indicates that under conditions of highly variable management (which are typical in tropical smallholder farming systems), QUEFTS may be most valuable as a predictor of attainable yield rather than average yield. We assume that the data used in this study – 1318 observations from farmer-managed NOTs in northern Nigeria – are representative of the empirical variability in yield response to nutrient management within smallholder systems of the region (*e.g.* Njoroge et al., 2019, 2017; Ojiem et al., 2014; Vanlauwe et al., 2011; Zingore et al., 2007). In this sense, our results are relevant for QUEFTS-based analysis elsewhere in Africa and other developing regions.

More concretely, we show that – under variable agronomic management conditions – the current standard approach for training or calibrating QUEFTS, involving standard linear regression of conditional mean yield responses, is inferior to calibration approaches based on quantile regression of conditional responses at the 90th percentile, which we use as a measure of attainable yield. A likely explanation is the underlying QUEFTS assumption on no other yield limiting factors than nutrients (Smaling and Janssen, 1993). This assumption is most likely at odds with the variability of plot-level conditions in SSA. Smallholder farming systems in Nigeria (and elsewhere) are characterized by a multitude of non-nutrient yield limiting factors, including pests, diseases, micro-climatic variability, and idiosyncratic management factors. Using planting density as an explanatory variable, part of the variation in observed yields for similar biophysical conditions could be explained. Causes of varying plant densities were not recorded for each field, but were, amongst other factors, caused by poor thinning, poor emergence due to drought and destruction by termites and other pests. Data validation approaches which ignore such non-nutrient yield limiting factors as sources of variability will be fundamentally challenged in predicting yield responses. We therefore argue that predicting attainable yields makes more sense than predicting yields in such conditions.

For practical applications, we present an alternative approach to empirically calibrating QUEFTS, using quantile regression. This method gives relatively robust predictions of attainable yields (90th percentile yields), after controlling for other biophysical factors. This makes intuitive sense, as the attainable yield conceptually corresponds to the yield one would attain after addressing other limiting factors. Additionally, this method can also be used to predict median yields (as shown in Fig. 8) or other percentiles, such as the 50th percentile. These, in combination with attainable yields, can provide a farmer with a realistic range of yield responses to nutrients applied considering other yield limiting factors in addition to soil nutrients.

Our findings are in contrast with results from (Shehu et al., 2019) based on the same data set. Shehu et al. (2019) found a good correlation between observed yields and predicted QUEFTS grain yields using standard linear regression for estimating indigenous soil nutrient's supply. However, in their analysis a Mahalanobis Distance outlier selection method was used to remove multivariate outliers (n = 434), aiming to reduce the variability in yield responses to soil parameters. Our study, in contrast, selects outliers based on observed extremities in plant parameters, taking the standardized residual size of a linear mixed model on plant parameters as a criterion (n = 52). In the latter case, fewer outliers are removed and more of the observed variation of yield responses remained in the dataset. More importantly, in this manner, no data is removed based on expected relationships between yield responses and co-variables.

Other studies found similar challenges in explaining yield variability when only biophysical conditions were taken into account. For example, Ichami et al. (2019) conducted a meta-analysis using 71 studies aiming to identify factors that could help to adjust fertiliser recommendation to the biophysical environment. They concluded that in SSA soil pH, exchangeable K and soil texture together explained less than 33 % of the variation in fertiliser recovery. In Kenya, Njoroge et al. (2017) found strong spatial patterns for yield responses to N, P and K fertilizers. Six different clusters were identified with different types of responses. Between these clusters however, no differences in mean soil properties were observed. In an additional analysis, yield response variation was partly attributed due to difference in historical manure management (Njoroge et al., 2019).

4.2. Limitations of this study

In the experimental set-up, a number of limitations occurred which could be improved in further studies. First, only one fertiliser rate was used in the field experiments, likely affecting the observed recovery as this depends partly on the level of nutrients applied (Zingore et al., 2007). Using a number of nutrient application levels, our recovery fractions could be validated for a wider range. This is especially relevant when considering current farming practices as fertiliser rates generally applied by farmers are lower than the amount of nutrients applied in our study (Liverpool-Tasie et al., 2017). Second, the experiments were conducted in two seasons, while a wider range of weather conditions could have assured a wider application of the boundary line model (Shepherd et al., 2018). This will be more important in very wet or very dry years as the conducted trials took place in relatively normal years, while potential crop yields might be strongly reduced in very dry years. Lastly, while unavoidable to the large scale of the study, multiple enumerators were used, potentially adding to the observed variation in fertiliser response (Vanlauwe et al., 2016).

4.3. Recommendations for further research

This study has been the first to estimate attainable maize yields based on biophysical factors such as soil OC, clay content, silt content and soil pH (Fig. 8). Even though attainable yields were predicted reasonably well based on biophysical factors, only partial explanation has been given for the causes in the variation of the remaining yield responses, as we were only able to include plant density as a factor in our analysis. This calls for further research into predicting crop yields under different limiting conditions. Other management factors could include sowing dates (Laux et al., 2010), weed and pest management or historic field management. If the previous season included manure use or cultivation of legumes, maize yields could have benefited from residual nutrient effects (Franke et al., 2018; Njoroge et al., 2019).

5. Conclusions

One among many reasons proposed for the low levels of fertiliser usage in sub-Saharan Africa is the poor tailoring of fertiliser recommendations, which are agronomically and/or economically suboptimal. Raising fertiliser usage in the region will require, in part, better fertiliser recommendations which, in turn, will require more accurate assessments of likely yield responses in different locations and management contexts. The large uncertainty and variation in yield estimates observed in this study call for modest claims on potential for calibration and validation of yield response models such as QUEFTS, if only biophysical data is available.

We show that, instead of predicting an expected response to a given fertiliser application in a certain field, an upper bound can be given of attainable yield, if farmers do everything else right in terms of other management. This latter option is a more cautious and sensible approach. Predicting attainable yields only, given certain soil conditions and fertiliser application, acknowledges the large variability observed in the field. However, this approach could easily be extended to predictions of yield responses at different levels – *e.g.* the 25th, 50th or 75th percentile of the yield distribution – which may correspond to differing levels of farming ability and/or resource endowments that constrain management decisions. This opens up a flexible framework for generating context-specific fertiliser recommendations, compared to those which assume 'perfect management' and no limiting factors other than nutrient supply. Our proposed methodology may therefore support improvement of scenario analyses, foresight studies or economic cost benefit analyses on nutrient management in tropical smallholder farming systems. In the current era of rapidly emerging opportunities for digital agriculture in developing regions, the scope for improved fertiliser application recommendations to have impact at scale is increasing. Providing more realistic recommendations will enhance the return on investments for all stakeholders involved, especially in the long run.

6. Data statement

The data used in this analysis are freely available from CIMMYT's Dataverse repository (https://data.cimmyt.org), or upon request from the authors.

Declaration of Competing Interest

The authors declare that they have no conflict of interest.

Acknowledgement

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Appendix A

Additional plots on step 1 of the QUEFTS model

A correlation was found between silt + clay content of the soil, soil OC and soil N (Fig. A1A). However, when soil N was related against apparent N supply no correlation was found (Fig. A1B).

Apparent P supply significantly increased with increasing soil available P (Fig. A2).

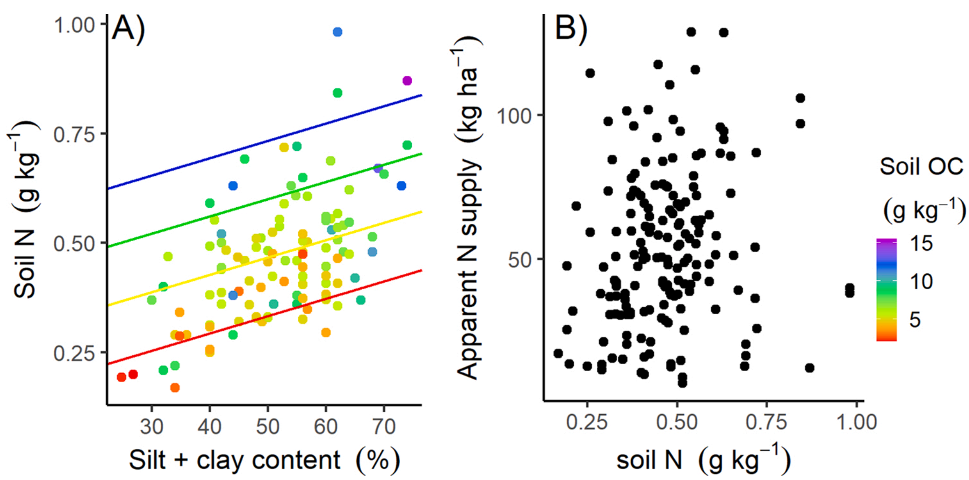

Fig. A1. Soil N (g kg^{-1}) against silt + clay content (%) (A) and apparent N supply (kg ha^{-1}) against soil N (g kg^{-1}). Different colours of the dots represent different levels of soil OC (in g kg^{-1}). Dot dashed lines indicate significant regression lines estimated with the linear mixed effects model with different levels of soil OC.

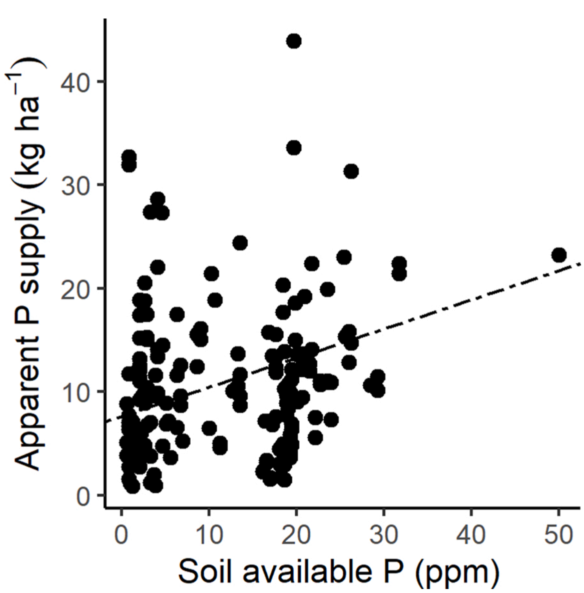

Fig. A2. Apparent P supply (in kg ha^{-1}) against soil available P (in ppm). The dot dashed line indicates the regression line estimated with a linear mixed effects model.

Appendix B

N, P and K supply validation plots using standard linear regression (B1) and quantile regression (B2).

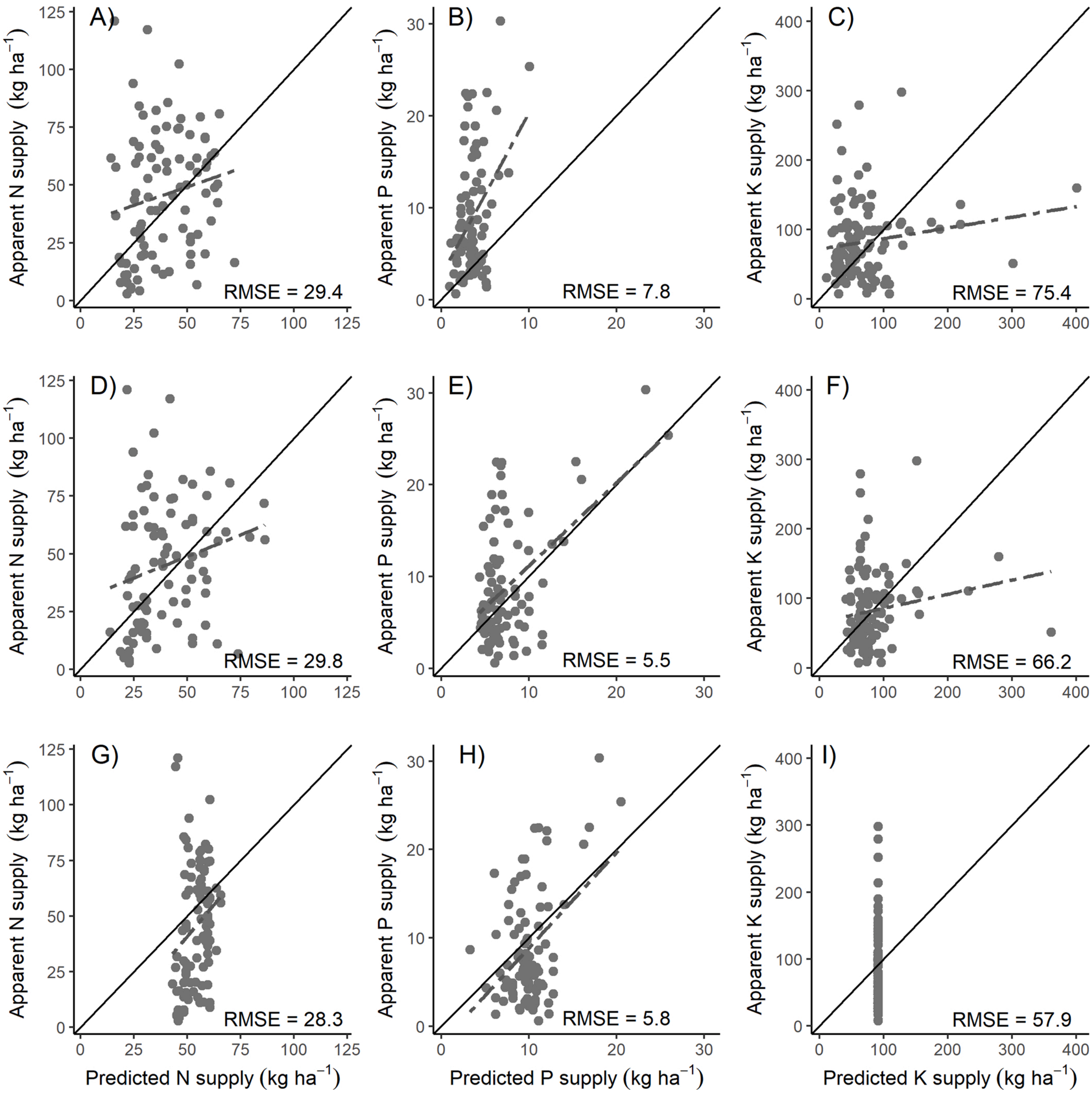

Fig. B1. Apparent nutrient supply of N, P and K against predicted nutrient supply of N, P and K respectively (in kg ha^{-1}). In the upper graphs (A, B, C) nutrient supply is predicted with QUEFTS equations. In the middle graphs (D, E, F) nutrient supply is predicted with equations calibrated by Shehu et al. (2019). The lower graphs (G, H, I) indicate predictions with equations found in this study. The solid black lines indicate the 1:1 line. The dot dashed lines indicate the regression lines.

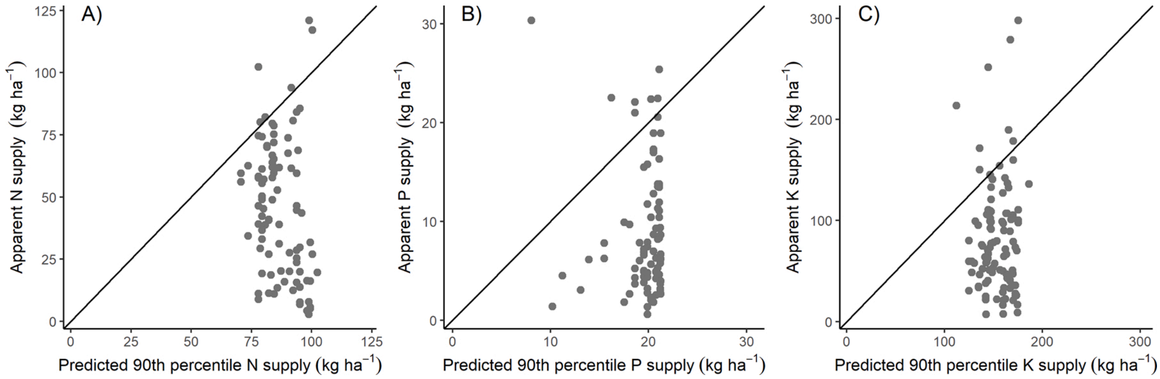

Fig. B2. Apparent N, P and K supply (in kg ha^{-1}) against predicted N, P and K supply (in kg ha^{-1}) respectively. The solid black line indicates the 1:1 line.

Appendix C

Relation between yield and plant density.
Fig. C1

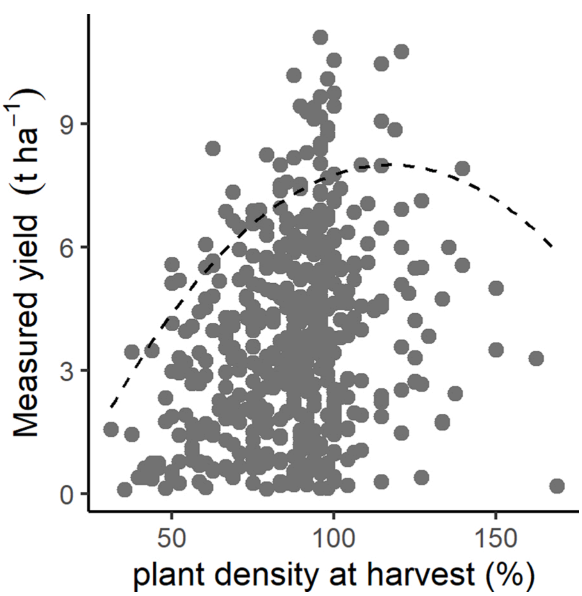

Fig. C1. Measured yield (in t ha^{-1}) against plant density at harvest (%). 100 % refers to 53 333 plants ha^{-1}. The dashed line indicates the boundary line of the 0.9 quantile.

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