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Compositional nutrient diagnosis and associated yield predictions in maize: A case study in the northern Guinea savanna of Nigeria

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Abstract

Developing optimal strategies for nutrient management of soils and crops at a larger scale requires an understanding of nutrient limitations and imbalances. The availability of extensive data (n = 1,781) from 2-yr nutrient omission trials in the most suitable agroecological zone for maize (*Zea mays* L.) in Nigeria (i.e., the northern Guinea savanna) provides an opportunity to assess nutrient limitations and imbalances using the concept of multi-ratio compositional nutrient diagnosis (CND). We also compared and contrasted the use of linear regression models and bootstrap forest machine learning to predict maize yield based on nutrient concentration in ear leaves. The results showed that 35% of the experimental plots had low yields due to nutrient imbalances (hereafter referred to as low yield imbalanced [LYI]). These experimental plots were dominated by control plots (without any nutrients applied),

Abbreviations: Av. P, soil available phosphorus content; CND, compositional nutrient diagnosis; CVA, critical value approach; DRIS, diagnosis recommendation and integrated system; ECEC, effective cation exchange capacity of soil; Fv, filling value; HYB, high yield and nutrient balanced group; HYI, high yield and nutrient imbalanced group; ICP-OES, inductively coupled plasma optical emission spectroscopy; −K, experimental treatment with omission of potassium and simultaneous application of nitrogen and phosphorus; LGA, local government area; LYB, low yield and nutrient balanced group; LYI, low yield and nutrient imbalanced group; −N, experimental treatment with omission of nitrogen and simultaneous application of phosphorus and potassium; NPK, experimental treatment with simultaneous application of nitrogen, phosphorus, and potassium; NPK+, experimental treatment in which secondary macronutrients (sulfur, calcium, and magnesium) and micronutrients (zinc and boron) were applied in addition to nitrogen, phosphorus and potassium; N_{tot}, soil total nitrogen content; −P, experimental treatment with omission of phosphorus and simultaneous application of nitrogen and potassium; SOC, soil organic carbon.

plots without N fertilization, and plots without P fertilization. Using the control plot as the ultimate indicator of nutrient imbalance, the significantly limiting nutrients in order of decreasing frequency of deficiency were N, P, S, Ca > Cu, and B. Both linear regression and bootstrap forest machine learning models fairly predicted maize grain yield based on nutrient concentration in ear leaves only in the LYI group and when examining all data with an independent validation dataset. These results suggest that nutrient management strategies, especially through the site-specific management approach, should consider S, Ca, Cu, and B in addition to the existing nutrients N, P, and K to improve nutrient balance and maize yield in the study area.

1 | INTRODUCTION

With the global decline in the availability and quality of arable land, optimal crop nutrition that ensures crops have access to sufficient amounts of all essential plant nutrients to produce higher yield per unit area is critical (FAO, 2017). Whether the essential nutrients are required in relatively high (macronutrients) or low (micronutrients) concentrations, none of them can be considered insignificant, as they all play an indispensable role in optimizing plant growth and development and/or the quality characteristics of the harvested product (Arnon & Stout, 1939; Brown et al., 2021; Marschner, 2012). One of the recognized laws in plant nutrition and production, Liebig's "law of the minimum" states that the deficiency of a single nutrient is sufficient to limit plant growth and productivity (Claupein, 1993). In addition, the supply of these essential nutrients to plants must be balanced, since an imbalanced supply due to natural and/or anthropogenic phenomena triggers nutrient interactions that can hinder the uptake and utilization of other nutrients, thus affecting plant growth, productivity, and quality. The assessment of nutrient imbalances in crops is therefore critical for the development of decision support and sound nutrient management strategies to improve not only crop yield and quality, but also nutrient use efficiency (Magallanes-Quintanar et al., 2006).

Various approaches such as visual deficiency symptoms, soil tests, and plant tissue tests are used to detect nutrient imbalances or deficiencies that help farmers make empirically based nutrient management decisions (Ichami et al., 2022). Assessing nutrient deficiencies based on visual symptoms of plants is a quick and inexpensive method. However, symptoms attributed to hidden starvation may be overlooked or misinterpreted if the deficiency symptom is associated with other plant stresses (e.g., pests and diseases) (Foster, 2001; Ichami et al., 2022). Soil testing is the most widely used approach for assessing nutrient deficiencies and developing fertilizer recommendations for arable crops (Roy et al., 2006). Often, low soil test values indicate a positive crop response to fertilization (Petersen et al., 2012). One of the main advantages of soil tests compared with other diagnostic methods for crop deficiencies is that nutrient deficiencies can be detected early, even before crops are grown. However, soil test values must be calibrated to plant response before they can be accurately interpreted (Havlin & Jacobsen, 1994), and sometimes other growth-limiting factors can interfere with the correlation between soil test results and plant nutritional status (Schut & Giller, 2020; Sinclair et al., 1997). Plant tissue testing to measure the nutrient concentration of growing plants reflects the current state of nutrient supply, which can serve either as a diagnostic function (to confirm or reject the presence of limiting nutrients in the soil highlighted by visual symptoms on the plants), a monitoring function (to ensure that growing plants always have adequate nutrient supply for optimal growth), or a supportive function (where it is used in conjunction with soil test results to make fertilizer recommendations) (Imakumbili et al., 2020). Although plant tissue testing provides more up-to-date plant-related information than soil testing, it is more costly and requires more effort in sampling, sample handling, and analysis (Roy et al., 2006). In addition, information on plant nutrient status from plant tissue testing is often obtained late in plant growth when the plant has already suffered from nutrient stress, so it is likely to be useful for the subsequent crop. Therefore, plant tissue testing can be considered a useful complement to soil testing (Nowaki et al., 2017).

Over the years, various methods have been developed to diagnose and interpret the nutritional status of plants based on plant tissue analysis. These methods include the critical value approach (CVA; Bates, 1971), the diagnosis recommendation and integrated system (DRIS; Walworth & Sumner, 1987), and the compositional nutrient diagnosis (CND; Khiari et al., 2001b; Parent & Dafir, 1992; Parent et al., 1993). The CVA is a univariate approach that establishes adequate nutrient concentrations based on a threshold at 90–95% of maximum yield (Ware et al., 1982). The CVA works well when only one nutrient is deficient because it does not consider the interactions between nutrients (Jones et al., 1991). The DRIS is a

bivariate method that uses dual nutrient ratios that reflect some degree of nutrient interactions (Walworth & Sumner, 1987). However, DRIS indices are empirical, without an accurate sketch of the covariance matrix for conducting multivariate statistical analyses, leading to potential misinterpretation when correlated with yield (Barłóg, 2016; Parent et al., 2012). Parent and Dafir (1992) proposed a multi-ratio CND concept based on compositional data analysis (Aitchison, 1982). Compositional nutrient diagnosis accounts for multiple and complex interactions among essential plant nutrients (Fageria, 2001) and accurately specifies a covariance matrix that allows multivariate calculation of ratios resulting from mutually exclusive nutrient concentrations (Parent, 2011), thereby avoiding possible misinterpretation in correlation with yield.

The agroecology of the northern Guinea savanna is the most suitable zone for maize (*Zea mays* L.) cultivation in Nigeria because it offers a relatively favorable combination of adequate rainfall, low night temperatures, and low incidence of potential pests and diseases (Badu-Apraku et al., 2015). Despite being the most suitable region, the average maize yield in farmers' fields in this region has been fluctuating around 1–2 t ha^{-1} for several decades (FAOSTAT, 2021). This value is much lower than the attainable yield of about 7 t ha^{-1} in well-managed experimental fields (Fakorede & Akinyemiyu, 2003; Sileshi et al., 2010) and far below the water-limited yield potential of 10.8 t ha^{-1} (GYGA, 2021). Similar to other sub-Saharan African regions, the large maize yield gap in this region is attributed to a variety of biophysical and socioeconomic factors, including inherent and/or induced low soil fertility, erratic rainfall, disease and pest infestation, poor agronomic management practices, limited access to agricultural inputs, and inadequate adoption of improved production technologies (Beah et al., 2021; Kamara et al., 2009; Njoroge et al., 2017). Among these factors, poor soil fertility and inadequate nutrient management are among the major causes of low maize yields in the region. To improve maize yields, nutrient management strategies need to be developed to ensure adequate and balanced supply of all limiting nutrients. However, to develop such nutrient management strategies, information on how, where, and why nutrient imbalances and limitations occur in maize at large scales is critical. Therefore, this study was conducted to diagnose nutrient limitations and imbalances in maize using foliar CND in the northern Guinea savanna region of Nigeria. Specifically, the objectives of this study were (a) to establish foliar nutrient sufficiency ranges for maize in northern Guinea savanna in Nigeria based on the CND approach, (b) to assess nutrient deficiencies and imbalances in maize in the northern Guinea savanna in Nigeria, and (c) to explore the possibility of predicting maize yield based on ear-leaf nutrient concentration dictated by nutrient imbalances from the CND in the northern Guinea savanna in Nigeria.

Core Ideas

- Thirty-five percent (n = 625 out of total 1,781) of the experimental plots have low yield due to nutrient imbalances.
- Nitrogen and P are the most yield limiting nutrients.
- Nitrogen, P, S, Ca > Cu, and B were the significant deficient nutrients in decreasing order of importance.
- Most of the obtained CND nutrient sufficiency ranges are comparable to ranges published in literature.
- Linear regression and bootstrap forest models perform fairly and comparably in yield prediction.

2 | MATERIALS AND METHODS

2.1 | Site selection, description, and experimental design

This study is based on data from 158 on-farm nutrient omission experiments conducted in two rainy seasons (2015 and 2016) in 12 local government areas (LGAs) of the northern Guinea savanna in Nigeria (Figure 1). The LGAs were selected to cover a wide range of maize growing conditions and include areas where research for development can support maize value chain programs in areas of high production potential in the northern Guinea savanna of Nigeria. The agroecological zone of the northern Guinea savanna is a subhumid to semiarid zone with an annual rainfall of 900–1,400 mm (Ayanlade, 2009). The predominant soil types in the region are Acrisols and Lixisols with variable proportions of Plinthosols and Cambisols (Dewitte et al., 2013). Average cumulative precipitation and average monthly minimum and maximum temperatures in the 12 focal LGAs are shown in Figure 2. The experimental plots were selected by creating one or two 10-km × 10-km grids in each study LGA (depending on the size of the county) using ArcGIS software (Environmental System Research Institute). Within each of these 10-km × 10-km grids, five 1-km × 1-km subgrids were uniformly delineated. In each of the 1-km × 1-km subgrids, one field was randomly selected for the experiment based on the willingness of a farmer and the availability of land for experimental setup. In each experimental field, two sets of experiments were established side by side, one with hybrid maize (hybrid) and the other with open-pollinated maize (OPV). The nutrient omission experiments were composed of six nutrient application treatments: (a) control with no nutrient application at all (control), (b) no N with simultaneous application of P and

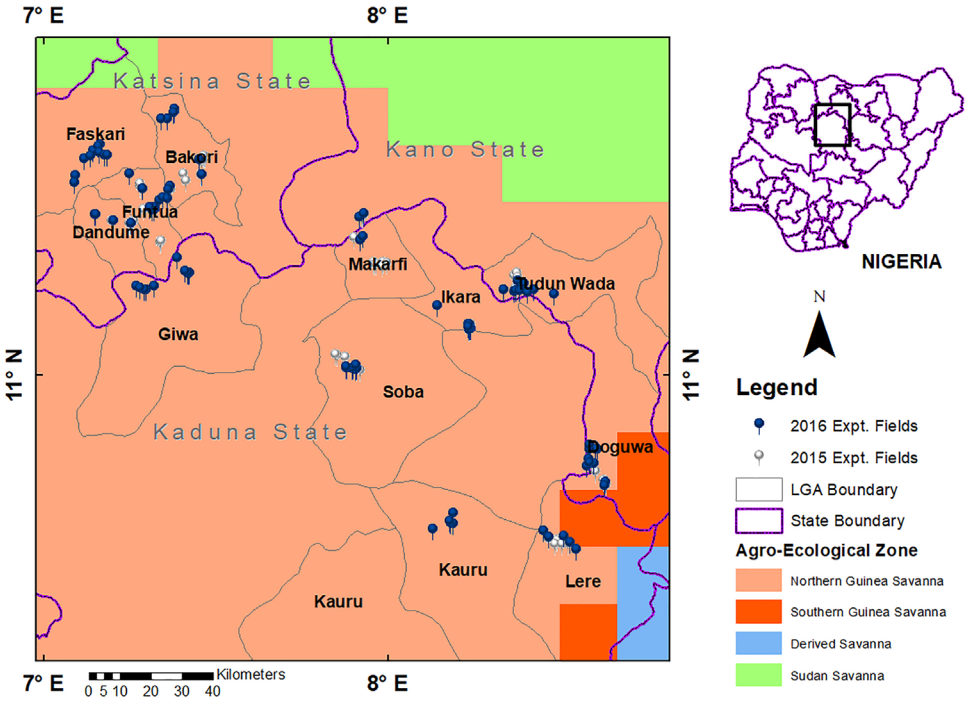

FIGURE 1 Map of Nigeria showing the study local government areas (LGA) and experimental fields where diagnostic nutrient omission trials were conducted during the 2015 and 2016 rainfed seasons

K (−N), (c) no P with simultaneous application of N and K (−P), (d) no K with simultaneous application of N and P (−K), (e) treatment with application of all three nutrients (NPK), and (f) treatment in which secondary macronutrients (S, Ca, and Mg) and micronutrients (Zn and B) were applied in addition to NPK (NPK+). Plot size was 5 m × 6 m (30 m^2) with plant spacing of 0.75 m (between rows) and 0.25 m (within rows). Detailed information on the experimental design and treatments can be found in Shehu et al. (2018, 2019).

2.2 | Field and laboratory measurements

2.2.1 | Soil data

From each experimental field, four soil samples were collected from a depth of 0–20 cm using the zig-zag principle when the experiment was set up prior to fertilizer application. The four collected samples were thoroughly mixed to obtain one disturbed composite sample per experimental field and passed through a 2-mm sieve for laboratory analysis. Total soil organic C was determined using a modified Walkley & Black chromic acid wet oxidation and spectrophotometric method (Heanes, 1984). Total N was extracted using a micro-Kjeldahl digestion method (Bremner, 1996), and the concentration was measured colorimetrically using an N-autoanalyzer (Technicon autoanalyzer II, SEAL Analytical). Soil pH in water (soil/water ratio 1:1) was determined using a pH meter with glass electrode, and particle size distribution was determined using the hydrometer method (Gee & Or, 2002). Available P, available S, exchangeable cations (K, Ca, Mg, and Na), and micronutrients (Zn, Fe, Cu, Mn, and B) were analyzed using the Mehlich-3 extraction method (Mehlich, 1984) followed by inductively coupled plasma optical emission spectroscopy (ICP-OES, Optima 800, Winlab 5.5, PerkinElmer). Exchangeable acidity (H + Al) was determined by extracting the soil with 1 N KCl and titrating the supernatant with 0.5 M NaOH (Anderson & Ingram, 1993). Effective cation exchange capacity (ECEC) was calculated as the sum of exchangeable cations (K, Ca, Mg, and Na) and exchangeable acidity (H + Al).

2.2.2 | Ear leaf data

For nutrient diagnostics in maize, it is generally accepted that the ear leaf is an organ with greater metabolic activity and its nutrient concentration is best related to maize yield (Jones, 1998). Therefore, a total of 10 ear leaves were randomly sampled from each experimental plot at the critical early stage of silking (reproductive stage "R1"). Ear leaves were sampled in the rows adjacent to the net plot (the net plot consists of four center rows of 3 m x 3 m for grain harvest). An ear leaf was removed by plucking it downward with moderate force (approximately at an angle of <30°) so that the leaf could be plucked at the collar, leaving the leaf base surrounding the stalk. The ear leaf samples were then washed with distilled water to remove impurities and oven dried at 60 °C for 48 h. The dried ear leaf samples were then ground into powder using an agate pestle and mortar. The powdered samples

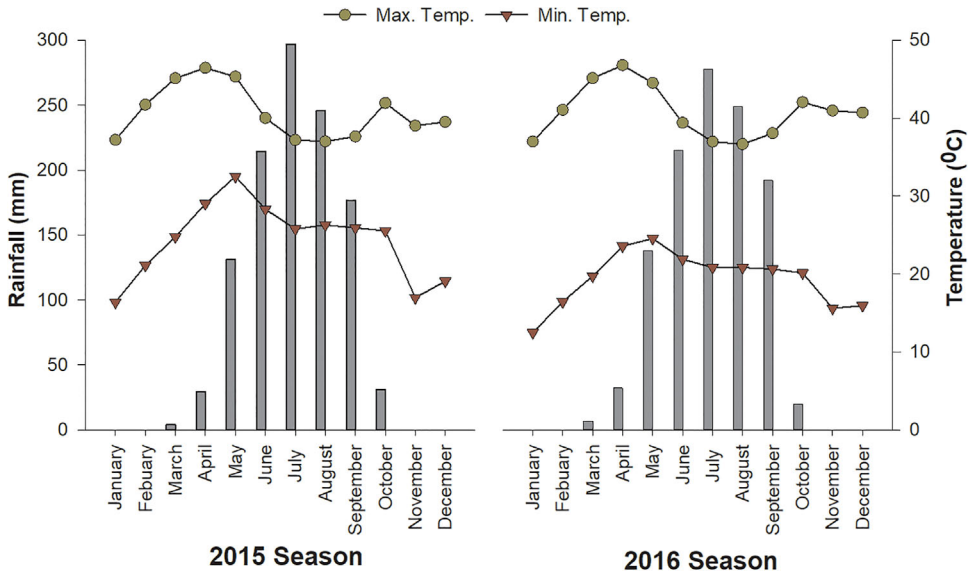

FIGURE 2 Monthly total rainfall and monthly average minimum and maximum temperatures in the studied districts in the northern Guinea savanna of Nigeria, recorded in two seasons of the experiment (i.e., 2016 and 2015)

were digested with nitric acid (HNO_3) and the concentrations of P, K, S, Mg, Ca, Zn, Cu, Mn, Fe, and B were determined by inductively coupled plasma optical emission spectroscopy (ICP-OES, iCAP 7000 Series, Thermo Scientific). Nitrogen concentration (N) was determined colorimetrically using an autoanalyzer (Technicon AAII, SEAL Analytical) according to the micro-Kjeldahl digestion method (Bremner, 1996).

2.2.3 | Yield data

Plants were harvested at physiological maturity from a net plot area of 9 m^2 (i.e., it included four middle rows of 3-m length of the experimental plot within the main plot), and the total fresh weight of the cobs was recorded. Ten cobs were then randomly selected as subsamples to account for grain shelling percentage and moisture content after air drying. Random selection was done by first counting the number of cobs in the net plot and then randomly arranging them in a row. The subsamples were then subsequently calculated at each interval as the total number of cobs in the net plot over the number of subsamples to be taken. Finally, grain yield was reported on a dry weight basis at a moisture content of 15.0%. The inferential statistics of the grain yield across the nutrient application treatments have been published by Shehu et al. (2019).

2.3 | Compositional nutrient diagnosis

Compositional nutrient diagnosis parameters were calculated based on the relationship between grain yield and the concentrations of eleven different nutrients (N, P, K, Mg, Ca, S, Cu, Fe, Mn, Zn, and B) in the maize ear leaf and the filling value (Fv) following the procedure described by Parent and Dafir (1992) and Khiari et al. (2001b). A filling value is 100% of the dry matter concentration minus the commutative fraction (%) of the 11 nutrient concentrations. A total of 1,781 samples (856 and 925 from the 2015 and 2016 experimental periods, respectively) across the experimental treatments were used for CND computation. First, the dataset (grain yield and corresponding nutrient concentrations in the ear leaf plus Fv) was arranged in decreasing order of the maize grain yield. Then, ear leaf nutrient concentrations, originally expressed in percentage units, were converted to row-centered log ratios (clr) according to Aitchison (1982) and Aitchison and Egozcue (2005). Subsequently, the CND parameters were calculated stepwise in Microsoft Excel 2016 and summarized below (for the detailed mathematical equations of each step parameter, the reader is referred to Parent and Dafir (1992) and Khiari et al. (2001b):

I. *Yield threshold separating the high yield subpopulation from the low yield subpopulation*: this was determined at the highest inflection point across the nutrient expressions (11 nutrients plus a Fv) from the cubic relationship between yield and cumulative variance ratio function of the nutrient expression. Statistical differences of grain yield and nutrient concentration between high-yield and low-yield subpopulations were evaluated using Student's *t* test.
II. *CND norms and indices*: CND norms are the threshold of nutrient's clr and were calculated as means and standard deviations of the nutrient's clr of the high-yield subpopulation. The CND indices represent deviations from the CND norms. A negative index indicates a low nutrient concentration compared with the norm and indicates a possible deficiency or imbalance.

III. *CND imbalance index (CND r^2)*: it measures the index of nutrient imbalance of the sample and was calculated as the sum of the squared of CND indices. The critical CND r^2 was determined from the allocation of the proportion of the low-yielding subpopulation as the exact probability of the chi-squared distribution function with 12 degrees of freedom (i.e., 11 nutrients plus a Fv). The maize yield cutoff or threshold value and the critical CND r^2 value can be used to categorize and interpret the grain yield and ear leaf nutrient composition data into four quadrants following Swets (1988). The four quadrants are: high yield and nutrient balanced (HYB) group, high yield and nutrient imbalanced (HYI) group, low yield and nutrient balanced (LYB) group, and low yield and nutrient imbalanced (LYI) group. High yield and nutrient imbalanced (HYI) group represents luxurious nutrient consumption, whereas LYB indicates that yield is limited by other factors but not nutrients (Parent et al., 2012).

IV. *CND nutrient sufficiency ranges*: these define adequacy of nutrient, with a fall below the range indicating nutrient deficiency and rise above the range indicating nutrient excess. The upper and lower boundaries of the CND nutrient sufficiency ranges were derived from the means and standard deviations of the sample nutrient concentrations with a CND r^2 below the critical value (i.e., nutrient balance subpopulation). The nutrient sufficiency ranges obtained from this study were also compared with the ranges published in the literature.

V. *Frequency and significant limiting nutrients*: the frequency of nutrients deficiency in the low yield and nutrient imbalanced (LYI) group were evaluated using the CND sufficiency ranges. However, to identify the major limiting nutrients, the average value of the individual nutrient index in the same LYI group was used and tested if the average value was significantly less than zero, indicating that the nutrient was significantly limiting, and vice versa (De Bauw et al., 2016; Khiari et al., 2001a; Parent et al., 1994). If normality of nutrient index was confirmed by Shapiro–Wilk *W* test in JMP statistical software version 14.0 (SAS Institute, 2017), then Student's *t* test was used to test whether the mean nutrient index is significantly below zero or not at $P \leq .05$. If normality of nutrient index was not confirmed, Wilcoxon's one-sample test was used to test whether the mean of nutrient index is significantly below zero or not at the same $P \leq .05$.

2.4 | Yield prediction based on nutrient concentration in the ear leaves

Prediction of grain yield based on nutrient concentration in ear leaves was evaluated by linear regression and bootstrap forest models using JMP statistical software version 14.0 (SAS Institute, 2017). To evaluate the potential influence of nutrient balance status on yield prediction, five datasets were used, including the total population data set and the four yield–nutrient balance subpopulation datasets (i.e., HYB, HYI, LYB, and LYI derived from CND Step IV above). In each of the five datasets, 75 and 25% of the data were randomly selected as independent model training and validation dataset, respectively. For the linear regression model, the best model was selected based on the highest coefficient of determination (R^2) and the minimum corrected Akaike information criterion (AICc) of the training dataset among five distribution functions (linear, polynomial, logarithmic, exponential, and Cauchy). The selection of nutrient in the linear regression was based on Lasso estimation method. For the bootstrap forest model, the best model was selected based on the lower out-of-bag error after testing four levels of trees (50, 100, 150, and 200) in the forest. Finally, the performance of the two models (linear regression and bootstrap forest) in the validation dataset was compared and contrasted using the RMSE, R^2, index of agreement (*d*) (Equations 1–3). The model with the best performance is the one with a smaller RMSE and a higher R^2 and *d* value.

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}\left(Y_i^{\mathrm{obs}} - Y_i^{\mathrm{pre}}\right)^2}{n}} \tag{1}$$

$$R^2 = \left(\frac{\sum_{i=1}^{n}\left(Y_i^{\mathrm{obs}} - \bar{Y}^{\mathrm{obs}}\right)\left(Y_i^{\mathrm{pre}} - \bar{Y}^{\mathrm{pre}}\right)}{\sqrt{\sum_{i=1}^{n}\left(Y_i^{\mathrm{obs}} - \bar{Y}^{\mathrm{obs}}\right)^2}\sqrt{\sum_{i=1}^{n}\left(Y_i^{\mathrm{pre}} - \bar{Y}^{\mathrm{pre}}\right)^2}}\right)^2 \tag{2}$$

$$d = \frac{\sum_{i=1}^{n}\left(Y_i^{\mathrm{obs}} - Y_i^{\mathrm{pre}}\right)^2}{\sum_{i=1}^{n}\left(\left|Y_i^{\mathrm{pre}} - \bar{Y}^{\mathrm{obs}}\right| + \left|Y_i^{\mathrm{obs}} - \bar{Y}^{\mathrm{obs}}\right|\right)^2} \tag{3}$$

where Y_i^{obs} = *i*th grain yield observed, $\bar{Y}^{\mathrm{obs}}$ = mean of the observed grain yield, Y_i^{pre} = *i*th grain yield predicted by the model, $\bar{Y}^{\mathrm{pre}}$= mean of the predicted grain yield, and n = number of observations.

3 | RESULTS

3.1 | Soil characteristics of the experimental fields

The soil properties of the experimental fields showed great variability, except for pH, which had a low CV of 8.2% (Table 1). Sand, silt, and clay contents in the fields ranged from 26 to 70%, 13 to 43%, and 13 to 42%, respectively;

TABLE 1 Descriptive statistics of selected chemical and physical properties of topsoil (0–20 cm) of fields where the on-farm nutrient omission trials were conducted

Soil parameter	Min.	Max.	Median	Mean	SD	CV
						%
pH (in water 1:1)	4.8	7.2	5.7	5.8	0.5	8.2
SOC, g kg^{-1}	2.4	15.5	6.3	7.0	2.4	34.9
N_{tot}, g kg^{-1}	0.25	0.98	0.44	0.46	0.13	29.00
Av. P, mg kg^{-1}	0.6	50.0	4.9	9.6	8.7	90.8
S, mg kg^{-1}	4.69	11.52	7.32	7.55	1.43	18.91
Ca, $cmol_c$ kg^{-1}	0.28	9.78	2.09	2.28	0.87	38.29
Mg, $cmol_c$ kg^{-1}	0.08	1.99	0.70	0.72	0.31	42.40
K, $cmol_c$ kg^{-1}	0.06	1.35	0.17	0.21	0.14	64.06
Na, $cmol_c$ kg^{-1}	0.04	0.09	0.09	0.08	0.02	21.22
EA, $cmol_c$ kg^{-1}	0.00	1.00	0.00	0.04	0.13	304.06
ECEC , $cmol_c$ kg^{-1}	1.23	11.06	3.17	3.33	1.03	30.78
Zn, mg kg^{-1}	0.83	37.52	6.86	7.94	5.77	72.74
Cu, mg kg^{-1}	0.76	5.12	1.66	1.89	0.90	47.60
Mn, mg kg^{-1}	3.71	158.46	28.48	33.04	21.51	65.11
Fe, mg kg^{-1}	43.36	527.18	121.80	158.25	94.53	59.74
B, mg kg^{-1}	0.00	0.12	0.02	0.03	0.02	74.71
Sand, %	26	70	46	47	10	21
Silt, %	13	43	31	30	8	25
Clay, %	13	42	22	23	5	23

Note. SOC, soil organic C; N_{tot}, total N; Av. P, available P; EA, exchangeable acidity; ECEC, effective cation exchange capacity.

however, on average, the fields had a loamy texture. On average, soil pH in the fields was in the moderately acidic range (pH 5.6–6.0). Soil organic C (SOC), total N (N_{tot}), available P (Av. P), ECEC, and available B contents were small and classified as low in the majority of the experimental fields according to the Nigerian Savanna Soil Fertility Classification by NSPFS (2005) and Esu (1991). Despite wide variability among fields, average contents of exchangeable bases (Ca, Mg, and K), available S, and available Cu were at intermediate levels according to the same Nigerian savanna soil fertility classification by NSPFS (2005) and ESU (1991). In contrast, the average contents of available Zn, Fe, and Mn in the experimental fields were in the range of high fertility.

3.2 | Compositional nutrient diagnosis

3.2.1 | Yield threshold and nutrient concentrations of the high- and low-yield subpopulations

The threshold or cutoff yield separating low and high yield subpopulations was obtained at the highest inflection point after examining a cubic cumulative–variance ratio functions of 11 nutrients and a filling value (Fv) vs. yield. The highest threshold yield was obtained for P with a value of 4.1 t ha^{-1}(Supplemental Table S1). Supplemental Table S1 also shows that the threshold value for K was negative and hence out of range. With this yield threshold at 4.1 t ha^{-1}, 46% of the total 1,781 observations belong to a high-yield subpopulation. Plots with NPK+, NPK, and −K (K omitted) nutrient application treatment were well represented in this subpopulation, contributing about 76% to this high-yield subpopulation. In contrast, the control, −N, and −P treatments dominated the low-yielding subpopulation (73%). The average grain yield of the high-yield subpopulations was significantly higher ($P \leq .05$) at 5.9 t ha^{-1} than that of the low yield subpopulations at 2.2 t ha^{-1}(Table 2), confirming that the 4.1 t ha^{-1} yield limit makes sense. In addition, the mean concentrations of all nutrients in the ear leaves, except Fe, were statistically higher ($P \leq .05$) in the high-yield subpopulations than in the low-yield subpopulation (Table 2).

3.2.2 | CND norms

The CND norms as means and standard deviations of the centered log ratios (clr) for high-yield subpopulations are shown in Table 3. Norms were negative for micronutrients and positive for macronutrients and Fv. Overall, the sum of the norms equals zero, indicating that the Cate Nelson yield-nutrient

TABLE 2 Average grain yield and ear leaf nutrient concentrations of the high- (HY) and low-yielding (LY) maize grain subpopulations based on compositional nutrient diagnosis (CND) yield partitioning procedure in the Nigeria's northern Guinea savanna

Variable	HY	LY	*F* value
Grain yield, t ha^{-1}	5.9	2.2	3,494.6**
Stover yield, t ha^{-1}	6.2	3.7	778.0**
Macronutrients, %			
N	2.50	2.01	438.9**
P	0.25	0.20	255.6**
K	2.03	1.94	21.0**
Mg	0.26	0.23	35.4**
Ca	0.60	0.49	225.6**
S	0.17	0.15	334.4**
Micronutrients, mg kg^{-1}			
Cu	6.70	5.93	61.5**
Fe	143.9	140.3	1.12
Mn	62.84	50.22	54.4**
Zn	14.08	12.80	31.7**
B	10.29	6.24	69.4**

Note. The *F* value is for the difference between HY and LY.
*Significant at the .05 probability level.
**Significant at the .01 probability level.

TABLE 3 Compositional nutrient diagnosis (CND) norms (V_x^*) for maize in the Nigeria's northern Guinea savanna

Nutrient	CND norms Mean	SD
Macronutrients		
V_N^*	3.38	0.17
V_P^*	1.07	0.21
V_K^*	3.17	0.24
V_{Mg}^*	1.09	0.28
V_{Ca}^*	1.95	0.21
V_S^*	0.71	0.12
Micronutrients		
V_{Cu}^*	−4.87	0.28
V_{Fe}^*	−1.82	0.30
V_{Mn}^*	−2.72	0.46
V_{Zn}^*	−4.12	0.24
V_B^*	−4.85	0.77
V_{Fv}^*	7.03	0.16
$\sum V_x^*$	0	–

Note. CND norms (V_x^*) are means and standard deviations (SD) of raw-centered, log ratios in a high-yielding subpopulation. Fv represents filling value.

response partitioning procedure (Nelson & Anderson, 1977) was performed correctly.

3.2.3 | Critical CND imbalance index and nutrient imbalance partitioning

According to a chi-square distribution function with 12 degrees of freedom (11 nutrients plus Fv), the critical CND imbalance index value (CND r^2) was 11.0 (Supplemental Figure S1). Values less than or equal to the CND r^2 indicate nutritionally balanced, whereas values above the CND r^2 show nutritionally imbalanced situations. Combining the grain yield cutoff and CND r^2, the experimental datasets were portioned into four quadrants (Figure 3). The LYI group accounted for the largest proportion (35%) of the experimental plots. Within the LYI group, 76% of the observations were from the control plots, −N, and −P treatments. The LYB group accounted for approximately 19% of the observations. Plots in this group showed that yield was limited by other abiotic and biotic constraints rather than nutrients. The HYI group, which indicates an excess of one or more nutrients, accounted for the smallest number of observations constituting just less than 18.6% of the experimental plots. Finally, the HYB group comprised 27.1% of the total 1781 observations. Within this HYB group, 76% of the observations came from the NPK+, NPK, and −K treatments.

3.2.4 | CND ear leaf nutrient sufficiency ranges

The maize nutrient sufficiency ranges obtained in this study for the northern Guinea savanna in Nigeria and comparison with the published literature sufficiency values obtained in other locations are presented in Table 4. In general, most of the ear leaf nutrient sufficiency ranges obtained in this study from the CND were within the published literature ranges, except for the upper limit for K and the lower limits for Cu and B, which were slightly higher and lower, respectively, than the ranges reported in the literature obtained from other locations.

3.2.5 | Maize nutrient limitations and imbalances

As described in Section 2.3, the experimental plots in the LYI group were used to evaluate the nutrients in the maize ear leaf that were significantly deficient or, if possible, in excess due to nutrient imbalance in the study area. The frequency of significant nutrient deficiencies in the different nutrient application treatments is shown in Table 5, whereas the frequency of excess in the same LYI group is shown in Table 6. The nutrients that were significantly deficient in the control plots ($n = 182$) without any nutrient application were, in order of decreasing frequency, N, P, S, Ca > Cu, B > Mn (Table 5). Overall, these deficiencies were found in over 60% of all control experimental plots. In the −N plots ($n = 165$), the

TABLE 4 Maize ear leaf nutrient sufficiency ranges in the Nigeria's northern Guinea savanna based on compositional nutrient diagnosis (CND) and comparison with published references

Nutrient	Northern Nigerian Guinea savanna		Njoroge et al. (2017)		Reuters & Robinson (1997)	
	LBL	UBL	LBL	UBL	LBL	UBL
Macronutrients, %						
N	2.12	2.88	2.09	2.34	2.30	3.30
P	0.20	0.30	0.26	0.29	0.17	0.32
K	1.71	2.38	1.67	1.87	1.71	2.25
Mg	0.20	0.33	0.15	0.17	0.13	0.24
Ca	0.49	0.71	0.45	0.51	0.21	1.00
S	0.15	0.20	0.15	0.17	0.16	0.22
Micronutrients, mg kg^{-1}						
Cu	5.35	8.55	7.40	8.30	6.00	20.00
Fe	100.91	169.26	–	–	30.00	200.00
Mn	32.49	84.00	68.91	77.30	20.00	150.00
Zn	10.80	17.28	10.67	11.97	18.00	60.00
B	4.14	13.06	11.10	12.45	5.00	25.00

Note. LBL, lower boundary limit; UBL, upper boundary limit.

TABLE 5 Frequency of ear leaf nutrients deficiency in the low yield and imbalanced maize subpopulation (LYI) in the Nigeria's northern Guinea savanna based on nutrient sufficiency ranges from this study

NAT	No. of plots	Frequency intervals, %								
		90–81	80–71	70–61	60–51	50–41	40–31	30–21	20–11	0–10
Control	182		**N**, **P**, **S**, **Ca**	**Cu**, **B**	**Mn**	Mg, Zn		K	Fe	
−N	165	**N**, **S**	**Cu**, **Zn**	**Ca**, **B**	Mg, **Mn**	P	Fe	K		
−P	126		**P**, **Ca**	**B**			N, **Mg**, S	Cu	K, Fe, Mn	Zn
−K	57		**B**	**K**, **S**	**N**, **Zn**		P, Cu, Fe	Mg, Ca		Mn
NPK	52		**B**	**N**	**S**, **Zn**	K	Cu	P, Mg, Ca	Fe	Mn
NPK+	43				**Cu**	**N**, **P**	K, **S**	**Mg**, **Ca**, Zn		Fe, Mn, B
Overall	625			**N**, **S**, **B**	**P**, **Ca**, Cu	Zn	K, Mg, **Mn**	Fe		

Note. NAT, nutrient application treatment. Nutrients in bold are those with indices being significantly below zero (indicating significantly limiting) based on Student's *t* test (if normality confirmed) or 'one-sample Wilcoxon signed ranked' test (if normality unconfirmed).

TABLE 6 Frequency of ear leaf nutrients in excess in the low yield and imbalanced maize subpopulation (LYI) in the Nigeria's northern Guinea savanna based on nutrient sufficiency ranges from this study

NAT	No. of plots	Frequency Intervals, %								
		90–81	80–71	70–61	60–51	50–41	40–31	30–21	20–11	0–10
Control	182							Fe	K	N, P, Mg, Ca, S, Cu, Mn, Zn, B
−N	165								P, K, Fe	N, Mg, Ca, S, Cu, Mn, Zn, B
−P	126					Zn		K, Cu, Fe	N, S, Mn	P, Mg, Ca, B
−K	57						Ca, Mn	Mg, Cu, Fe	P	N, K, S, Zn, B
NPK	52						Cu, Fe	P, Ca, Mn	Mg, Zn	N, K, S, B
NPK+	43	B					Mn, Zn	P, K, Mg	N, Ca, S, Fe	Cu
Overall	625							Fe	K, Mg, Cu, Mn, Zn, B	N, P, Ca, S

Note. NAT, nutrient application treatment.

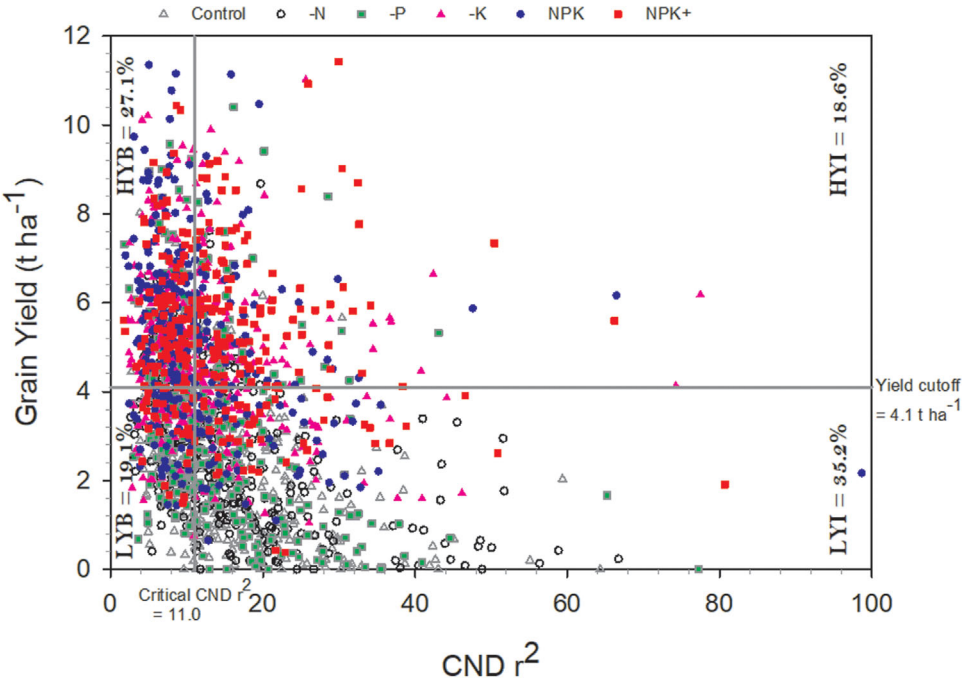

FIGURE 3 Portioning of data into four quadrants based on the relations between the cutoff yield (separating high and low yield subpopulation according to their nutrient balances) and critical compositional nutrient diagnosis balance index (CND r^2) for maize in the Nigeria's northern Guinea savanna. HYB, high yield and nutrient balanced group; LYB, low yield and nutrient balanced group; HYI, high yield and nutrient imbalanced group; LYI, low yield and nutrient imbalanced group

significant limiting nutrients in decreasing order of frequency of deficiency were as follows: N, S > Cu, Zn > Ca, B > Mn (Table 5). These deficiencies account for about 55% of all −N plots. In the −P plots (n = 126) of the same LYI, the significant limiting nutrients were the following in decreasing order of frequency: P, Ca > B > Mg. These significantly limiting nutrients occurred in 43% of all −P plots. In the −K experimental plots of the LYI group (n = 57), B > K, S > N, and Zn were the significantly deficient nutrients in decreasing order of frequency. These deficiencies affected only 17% of all −K plots. In the NPK plots (n = 52) that were still in the same LYI group, the statistically deficient nutrients were in decreasing order of frequency: B > N > S, and Zn. This was observed in only 17% of the total NPK plots. In the plots (n = 43) where secondary macro- and micronutrients (S, Ca, Mg, Zn, and B) were added to the NPK (NPK+), the significantly deficient nutrients from the same LYI group ranked in decreasing order of frequency: Cu > N, P > S > Mg, and Ca. These nutrient deficiencies occurred in NPK+ in only 15% of the total plots. With the exception of B in the NPK+ plots and Zn in the −P plots, the frequency of one or more nutrients found to be in excess is <40% of all plots in the LYI group (Table 6). In −P plots, Zn is present in excess in 50–41% of plots, whereas in NPK+ plots (within the same LYI group), 81–90% of samples (n = 43) had excess concentrations of B.

The correlation coefficients between soil characteristics and nutrient concentration in the ear leaf of the control plot of LYI are shown in Table 7. A positive but weak correlation was found between the concentration of N, P, C, and Cu in the soil and in the ear leaf. In the same trend, a positive correlation was observed between SOC and the concentration of K and Fe in the ear leaf. In contrast, a negative but weak correlation was recorded between SOC and the concentration of P, Ca, and B in the ear leaves. Soil pH had a positive effect on the concentration of P and Zn in the ear leaf. Soil texture, particularly clay content, affected nutrient concentration in the maize ear leaf, with a positive correlation between soil clay content and N, Mg, S, and Cu content in the ear leaf and a negative one with P concentration in the ear leaf. However, a positive correlation coefficient of .42 was found between soil sand content and P concentration in the ear leaf. Other positive correlations worth mentioning are between the P available in the soil and the B content in the ear leaf, and between the N_{tot} content in the soil and the S content in the ear leaf.

3.3 | Yield prediction based on nutrient concentration in the ear leaves

The linear regression models for predicting maize grain yield based on nutrient concentration in the ear leaf for different data sets (nutrient balance groups) are shown in Table 8. In the linear regression, N and P have a positive contribution to grain yield in the different data sets (Table 8). Potassium has

TABLE 7 Spearman correlation coefficient between soil characteristics and concentration of nutrients in the maize ear leaf of control plots of low yield and nutrient imbalanced group (LYI)

	Concentration of nutrient in the maize ear leaf										
Soil characteristic	**N**	**P**	**K**	**Ca**	**Mg**	**S**	**Cu**	**Fe**	**Mn**	**Zn**	**B**
pH (in water)	−.11	.19*	.13	.05	.02	−.07	−.13	.14	−.22	.21**	.10
SOC	.07	-.24**	.25**	−.18**	−.10	−.03	−.01	.20**	−.04	.01	−.21**
N_{tot}	.15*	−.07	−.07	.09	.12	.20**	.27**	.09	−.01	.05	−.01
Av. P	.09	.30**	−.23**	.30**	.08	.08	.13	−.17*	−.01	−.08	.15*
S	.16	−.10	.01	.04	.19**	.10	.11	.1	.08	.04	.04
Ca	.12	.11	−.10	.17*	.17*	.06	.03	.06	−.12	.08	.09
Mg	.01	−.11	−.04	−.07	.10	.09	.14	.05	−.23**	.09	.12
K	−.19	.05	.03	−.04	−.12	−.19	−.15*	.12	−.05	−.03*	.14
ECEC	.11	.07	−.1	.13	.16*	.07	.07	.08	−.16*	.07	.14
Zn	−.03	.20**	−.16*	.12**	.01	−.04	.01	−.16*	−.16*	.03	.06
Cu	.01	−.13	.17*	−.20	−.12	−.09	.17*	.08	.02	.07	−.06
Mn	.03	.07	−.35**	.11	.14	−.01	.14	−.05	.06	−.12	.13
Fe	−.02	.15*	.09	.07	−.11	−.09	−.13	−.01	.14	−.11	.01
B	−.03	.11	.05	−.10	.04	−.01	.06	−.02	−.01	.16	.02
Sand	−.32**	.42**	.03	−.05	−.23**	−.26**	−.25**	−.09	.07	−.07	−.05
Silt	.24**	−.31**	−.04	.06	.12	.198	.15*	.07	−.09	.14	.10
Clay	.23**	−.32**	.01	.01	.24**	.22**	.24**	.08	−.01	.08	−.05

Note. SOC, soil organic C; N_{tot}, total N; Av. P, available P; ECEC, effective cation exchange capacity;.
*Significant at the .05 probability level.
**Significant at the .01 probability level..

TABLE 8 Linear regression models of maize grain yield prediction from ear leaf nutrient concentrations

Group (dataset)	Model equation	Model R^2
All Data	Grain yield (t ha^{-1}) = −4.284 + 1.562 N (%) + 5.673 P (%) + 0.920 K (%) – 2.632 Mg (%) + 4.511 Ca (%) + 5.032 S (%) – 0.095 Cu (mg kg^{-1}) – 0.003 Fe (mg kg^{-1}) – 0.0012 Mn (mg kg^{-1}) – 0.02 Zn (mg kg^{-1}) + 0.0094 B (mg kg^{-1})	.48
HYI	Grain yield (t ha^{-1}) = 3.287 + 0.706 N (%) + 1.974 P (%) + 0.428 K (%) – 2.079 S (%) – 0.0779 Cu (mg kg^{-1}) + 0.019 Zn (mg kg^{-1})	.16
LYI	Grain yield (t ha^{-1}) = −1.168 + 0.450 N (%) + 2.998 P (%) – 2.915 Mg (%) + 4.331 Ca (%) + 0.0293 Cu (mg kg^{-1}) + 0.003 B (mg kg^{-1})	.51
HYB	Grain yield (t ha^{-1}) = 0.525 + 1.128 N (%) + 3.046 P (%) + 0.979 K (%) - 2.132 S (%) – 0.088 Cu (mg kg^{-1}) + 0.062 Zn (mg kg^{-1})	.24
LYB	Grain yield (t ha^{-1}) = 0.815 + 0.400 N (%) + 3.378 P (%) – 3.001 Mg (%) + 2.268 Ca (%) + 0.112 Cu (mg kg^{-1}) – 0.004 Fe (mg kg^{-1}) + 0.005 Mn (mg kg^{-1}) – 0.058 Zn (mg kg^{-1}) + 0.029 B (mg kg^{-1})	.26

Note. HYB, high yield and nutrient balanced group; LYB, low yield and nutrient balanced group; HYI, high yield and nutrient imbalanced group; LYI, low yield and nutrient imbalanced group. The explanatory parameters in the regression equations are nutrient concentration in the maize ear leaf.

a positive contribution in the linear regression model for all data, HYI, and HYB, although its effect was not observed in LYI and LYB. Sulfur had a positive contribution to the linear model when all data groups were considered and a negative effect in HYI and HYB. A positive contribution from Ca and B was observed in the entire data group, LYI, and LYB, whereas it was absent in the remaining models (i.e., HYI and HYB). A negative coefficient was observed for Mg for all data, LYI, and LYB, whereas it had no significant effect in the remaining datasets. Copper has a positive contribution to the linear model in LYI and LYB and a negative one in the rest of the group (data sets). Zinc has a positive contribution in HYI and HYB and a negative contribution in the remaining datasets (groups) to the same linear model of the region.

Manganese has a positive contribution in the linear regression model of LYB and a negative contribution when all data are considered. Iron has a negative coefficient in all datasets and the LYB group and is not present in the linear regression models of the remaining nutrient balance groups.

The contribution of each nutrient to the bootstrap forest model for the different data sets is shown in Supplemental Figure S2. Bootstrap forest models in Java Script format can be accessed by following this link. When considering the entire dataset, N, P, S, and Ca have the highest contribution (more than 12%) to the bootstrap forest model, whereas Fe and Mg have the lowest contribution. Nitrogen, P, and Ca are among the highest contributors to the bootstrap forest model in the four nutrient balance groups (i.e., HYI, LYI, HYB, and LYB). Similarly, unlike Zn, S is also among the highest contributors to the bootstrap model in the four nutrient balance groups except HYI. Potassium is among the leading contributors to the bootstrap forest model only in HYB and LYB. Although Mn is among the top contributing nutrients except in LYI. Boron, Mg, and Fe contributed least to the bootstrap forest model in all four nutrient imbalance groups.

The two models (linear and bootstrap forest) performed quite fairly and comparably in LYI and when all data were examined using an independent validation dataset (Figure 4). However, the two models did not perform well in the other nutrient balance groups, particularly in HYB and LYB where no nutrient imbalances or limitations were observed. Despite the generally poor performance of the two models, the linear model outperformed the bootstrap forest model in the HYI, HYB, and LYB groups when the index of agreement is used as a measure.

4 | DISCUSSION

4.1 | Soil characteristics of the experimental fields

Medium-textured soils are reported to be optimal for maize cultivation (Akinyele & Adigun, 2006); therefore, the average loamy texture of the experimental fields indicates that the fields are ideal for maize cultivation. The relatively high sand content in the soils was not a surprise, as soils in the region were reportedly formed from aeolian material and Precambrian basement complex rocks (such as granite, schist, and sandstone) (Bennett, 1980). Furthermore, Malgwi et al. (2000) reported that sorting of soil material due to clay eluviation and wind erosion as additional factors leads to high relative sand content in the surface soils of the northern Guinea savanna in Nigeria. The overall low contents of SOC, N_{tot}, Av. P, ECEC, and B in the soils can be attributed to two main factors: (a) the nature of the parent material and the intensive weathering of the soils with low mineral reserves required for inherent nutrient enrichment, and (b) the intensive cultivation of the soils with inappropriate (unbalanced and inadequate external input) nutrient management, including burning or complete removal of crop residues (Jones & Wild, 1975; Kwari et al., 2011; Manu et al., 1991; Smaling et al., 1991). The moderate average contents of exchangeable cations (Ca, Mg, and K) are not surprising, since most soils were formed from complex bedrock that contains high levels of these cations. Møberg and Esu (1991) also reported a considerable occurrence of K-containing feldspar minerals in sand and silt particles of savanna soils in Nigeria. Although the average content of micronutrients (Cu, Zn, Mn, and Fe) in the soils was moderate to high, some fields have low contents of Cu in particular. The low content of micronutrients in some fields is in agreement with the findings of Oyinlola and Chude (2010) and was attributed to poor nutrient management practices such as unbalanced application of one or more macronutrients depleting the reserves of the other micronutrients.

4.2 | Compositional nutrient diagnosis

4.2.1 | Grain yield cutoff and nutrient concentrations of the high- and low-yield subpopulations

The cutoff yield obtained in the CND analysis of this study, which separates a high-yielding from a low-yielding subpopulation, is similar to the 4.1 t ha^{-1} obtained by Njoroge et al. (2017) for long-season rainfed maize in western Kenya. The dominance of NPK+, NPK, and −K plots in the high-yield subpopulation with large concentrations of N and P in the ear leaves indicates these two elements as the most yield limiting for maize production in the study area. Soil organic matter (indicated by SOC), N_{tot}, and Av. P values are low in most of the studied fields, which explains the large yield responses to N and P addition. The substantial number of −K plots in the high-yield subpopulation suggests that K is a less important limiting nutrient for maize yield in the study area compared with N and P. Soil exchangeable K content is actually above the critical soil requirement of 0.16 $cmol_c$ kg^{-1} for maize in a greater number of the fields studied (Agboola & Ayodele, 1985). The low response of maize yield to K addition is also consistent with the work of Adediran and Banjoko (1995). The absence of significant differences in Fe concentration in the maize ear between the high-yielding and low-yielding CND subpopulation could also be related to the high Fe content in the experimental fields (43–527 mg kg^{-1} as shown in Table 1), which is far above the critical value of 5.0 mg kg^{-1} for maize reported in the literature (Farshid, 2012).

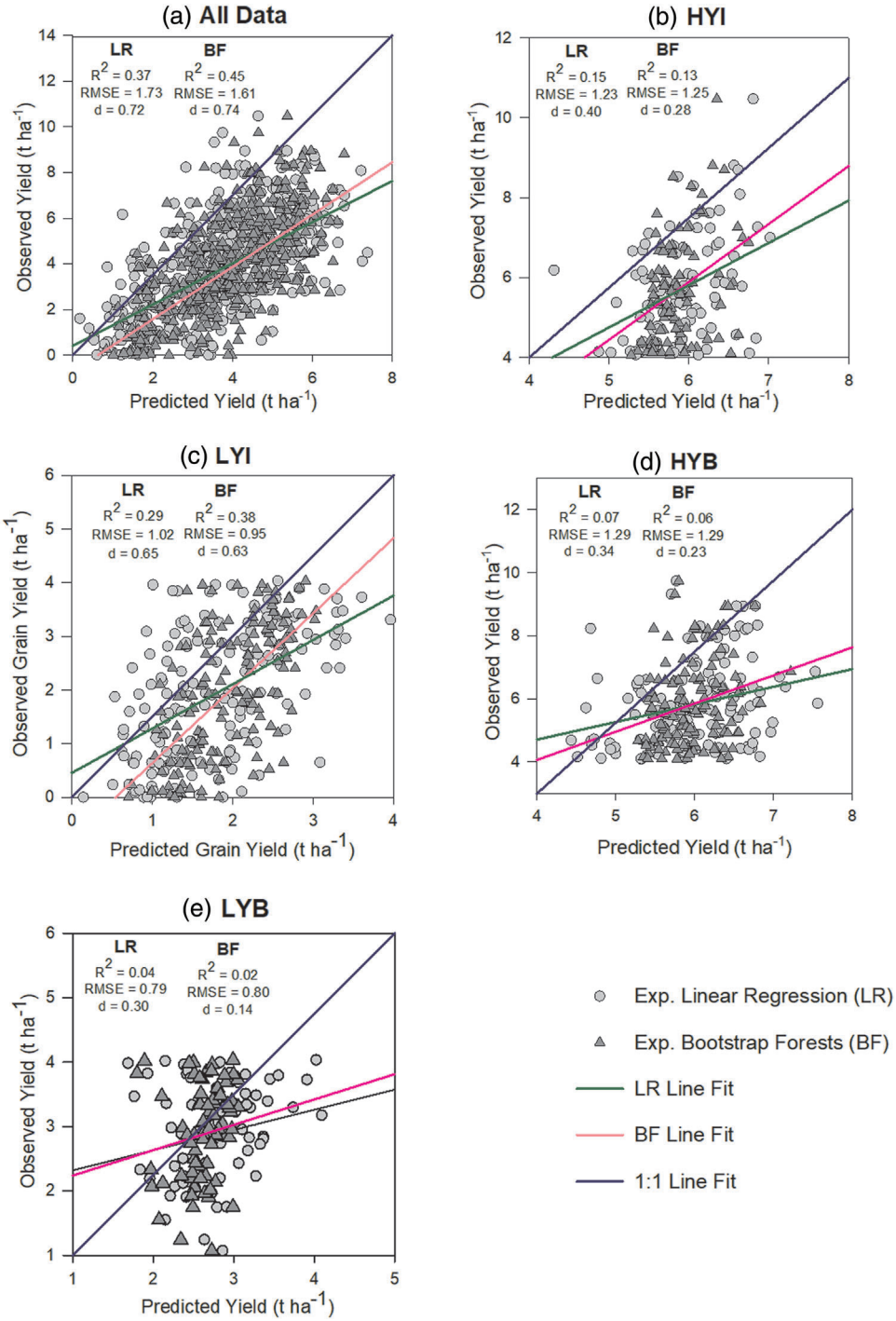

FIGURE 4 Observed maize grain yield against predicted yield based on ear leaf nutrient concentration of the independent validation dataset: (a) all data (all group), (b) high yield and nutrient imbalanced group (HYI), (c) low yield and nutrient imbalanced group (LYI), (d) high yield and nutrient balanced group (HYB), and (e) low yield and nutrient balanced group (LYB). d = index of agreement

4.2.2 | CND norms, critical CND imbalance index, nutrient imbalance partitioning, and CND ear leaf nutrient sufficiency ranges

Although slightly different, the values and trend of CND norms from this study are close to those obtained by Gott et al. (2017) and Njoroge et al. (2017). However, the minor differences between the norms could be related to variations in the prevailing climatic conditions, genotypes, and crop management. The most striking observation in the distribution of nutrient imbalances in the maize ear leaf is that about 35% of the experimental plots in the study area (including

primarily the control, N, and P plots) ended up in the LYI quadrant. This indicates that tremendous maize yield losses occur due to nutrient imbalances, which in turn are a result of inadequate supply of nutrients (especially N and P). However, the occurrence of some NPK+, NPK, and −K plots in the same LYI quadrant suggests that in certain cases, the supply of these nutrients is either inadequate or no longer available to the crop due to various losses such as leaching, fixation, and so on. In addition, there are also a significant number of fertilized plots in the HYI quadrant, suggesting that uniform or blanket application of fertilizer in the study area may lead to nutrient imbalances despite good yields due to spatial and temporal variability among fields. It follows that balanced nutrient supply can be achieved if fertilizer applications in the study area are tailored to the specific needs of the fields. Also, optimization of maize yields in the northern Guinea savanna zone of Nigeria requires attention to other limiting factors such as water stress, pests and diseases, agronomic management practices, and so forth, in addition to nutrient supply.

The differences between observed and published CND ear leaf nutrient sufficiency levels in the literature (especially evident for K, Cu and B) are due to differences in soil, climate, and maize varieties (Agboola & Ayodele, 1985; Njoroge et al., 2017). As also explained by Sahrawat (2006), the discrepancies between nutrient sufficiency levels in different areas are largely due to differences in nutrient concentrations influenced by growing conditions (such as climate and soil), nutrient supply, their interactions, and the cultivar grown.

4.2.3 | Maize nutrient limitations and imbalances

Using the control (no nutrient application) plots in the LYI as the ultimate indicator of an existing nutrient imbalance, the major nutrient deficiencies in the northern Guinea savanna zone of Nigeria are N, P, S, Cu, B, and Mn. As described above, N and P deficiencies in maize in the Nigerian savanna have been reported in several research papers (Aliyu et al., 2021; Ekeleme et al., 2014; Kamara, 2017; Nziguheba et al., 2009). Due to the low levels of these nutrients (N and P) in the soil and the positive relationship between soil and ear leaf content, optimization of soil content is crucial to correct limitations and maximize yield. In fact, despite the addition of N and P in the respective fertilized plots, some nutrient deficiencies were still found in this study. This means that either fertilizer rates were insufficient or fertilizer use efficiency was low. Low N and P use efficiency was frequently reported in the study area (Ravensbergen et al., 2021; Shehu et al., 2019; Tabi e et al., 2008). Sulfur deficiency in maize on West African savanna soils, including the northern Guinea savanna in Nigeria, has been similarly reported by Friesen (1991), Ojeniyi and Kayode (1993), Schulz et al. (2002), Nziguheba et al. (2009), and Aliyu et al. (2021). The application of S in the NPK+ plots in this study significantly reduced the incidence of S deficiency in the study area from >70% to <40%. However, soil N content rather than S content was found to contribute positively to S uptake in the ear leaf. This explains the synergistic relationships between S and N. The synergistic interaction between N and S is not surprising because the assimilation of N and S are closely related and strongly influence each other (Hawkesford et al., 1995; Zhao et al., 1997). Therefore, optimization of soil N supply can significantly reduce S deficiency. A considerable number of the studied fields have Cu and B content in the soil below the critical value for maize of 1.0 and 0.3 mg kg^{-1}, respectively, according to Sillanpää (1982). Therefore, the deficiency of Cu and B is not surprising. Ayodele and Omotoso (2008) and Eteng et al. (2014) found Cu deficiency in some parts of Nigerian savanna soils. Similarly, widespread B deficiency was found in some parts of savanna soils in northern Nigeria (Aliyu et al., 2021; Kihara et al., 2016; Oyinlola & Chude, 2010). Copper and B deficiencies are common in many cereals and occur either as severe deficiencies affecting vegetative organs or as mild deficiencies (hidden starvation) affecting the reproductive potential of plants (Njoroge et al., 2017). The Mn deficiency in the control (unfertilized) plots of LYI remains puzzling, since the soils of the study fields have high contents of this nutrient (3.71–158.46 mg kg^{-1} and an average of 30.9 mg kg^{-1}, as shown in Table 1). Therefore, it seems better not to overestimate this nutrient, also because the lower limit of the sufficiency ranges of the nutrient in the study area was almost double the values reported by Ojeniyi and Kayode (1993) in a similar environment. Despite the low response of maize yields to K application as described above, more than 60% of the −K plots had significant K deficiency in the LYI. This indicates that the addition of K to maize in the northern Guinea savanna of Nigeria based on site-specific nutrient management principles is still necessary to ensure balanced nutrient supply and interaction, and to avoid depletion of K reserves in the future. Also, addition of soil organic matter can significantly help in correcting marginal K deficiency and ensure nutrient balance, because the observed positive (but weak) correlation between SOC and ear leaf K content is significant. The weak negative correlations between SOC and ear leaf P, C, and B contents remain puzzling in this study and may be related to other biophysical and chemical factors influencing soil–plant interactions that were not considered. Schut and Giller (2020) and Sinclair et al. (1997) reported that other growth-limiting factors can interfere between soil test results and plant nutritional status.

4.3 | Yield prediction based on nutrient concentration in the ear leaves

The fair and comparable performance of the linear and bootstrap forest models in LYI and the entire dataset suggests

that either model can be used to predict grain yield based on nutrient concentration in ear leaves in the study area. The fair performance of the two models in LYI is not surprising since this is a group where low yields and simultaneous nutrient imbalance exist, so adding nutrients will significantly increase grain yield. The poor performance of the two models in HYI, HYB, and LYB is not surprising because HYI represents luxury nutrient use, whereas in HYB, there is no nutrient limitation and no luxury use, while in LYB, yield is limited by other biophysical factors and management failures (such as water, temperature, pests, and diseases) and not by nutrient supply.

The observed negative or positive coefficients of nutrients in the linear regression model and the different contributions of nutrients to the bootstrap forest model in the nutrient balance groups of the CND indicate different forms of interaction of nutrients affecting the growth and yield of maize under different conditions of nutrient availability and balance. The most striking interaction is among N, P, S, and Ca, which contribute positively to grain yield in the linear regression and make the largest contribution to grain yield when the entire dataset is considered in the bootstrap forest regression model. This indicates a synergistic relationship among the four nutrients (i.e., N, P, S, and Ca) regardless of the nutritional status of maize in the study area. Most interactions between nutrients reported in the literature are dual or bivariate interactions, with an overall lack of information on the effects of interactions between multiple nutrients on plants (Fageria, 2001; Rietra et al., 2017). Several studies have reported positive interactions between N and P, N and S, and P and Mg (Fageria, 2001; Rietra et al., 2017). Although the mechanisms leading to positive interaction of N and P are poorly understood (Fageria, 2001), many scientists have conceptually contributed this to synergistic growth responses (Schleuss et al., 2020). The synergistic interaction between N and S is not surprising because the assimilation of N and S is closely related and strongly influences each other (Hawkesford et al., 1995; Zhao et al., 1997). This is because both N and S play a central role in the synthesis of proteins in the plant (Jones, 2012). A positive interaction between P and Mg is expected because Mg is an activator of kinase enzymes that initiate most reactions involving phosphate transfer (Fageria, 2001). Potassium, along with N, P, S, and Ca, has a positive effect on maize grain yield when total data and HYB and HYI nutrient balance or imbalanced portioned groups are considered. Moreover, the five nutrients (N, P, S, Ca, and Mg) in the same bootstrap forest models for HYI and HYB groups are among the most important factors in the model. The synergistic interaction between N and K has been widely reported and is attributed to the involvement of K in NO_3^- uptake, which is the predominant form of N in soil (Fageria, 2001; Fageria & Oliveira, 2014). For other nutrients where a negative coefficient was observed for the grain yield prediction models in the different balanced and unbalanced nutrient groups, this can be attributed to interactive dilution and accumulation effects influenced by different biophysical factors and nutrient application treatments in the study. For example, Mn concentration in the ear leaf was found to have a positive coefficient in the linear model of LYB and a negative coefficient in the other nutrient balance groups. The average Mn concentration in LYB is 20% lower than in the other groups. Therefore, the positive coefficient of the linear regression model for Mn could be attributed to a deficiency of this nutrient and vice versa in the other nutrient balance groups.

5 | CONCLUSION

From the results of this study, it appears that (albeit with variations from field to field) N, P, S, Cu, and B are the most important nutrient deficiencies overall in maize from the CND analysis in the northern Guinea savanna region of Nigeria. Potassium was also not among the significantly limiting nutrients in the CND analysis, but >70% of plots where K was not applied (−K) developed significant K deficiencies. Investing in site-specific nutrient management practices based on integrated soil fertility management principles will radically correct the identified nutrient limitations and imbalances. The benefits would come from optimizing and maintaining nutrient use efficiency and yield by supplying all limiting nutrients and avoiding over- or underapplication of fertilizer. In the same vein, the established nutrient sufficiency ranges in the maize leaves from the CND analysis in the study area can provide a quick and easy guide for identification of nutrient deficiencies and real-time nutrient management.

This study also found that both linear regression and bootstrap forest machine learning models predicted maize grain yield fairly and comparably based on nutrient concentration in ear leaves only in the LYI category and when the whole data were examined using an independent validation dataset. With the emerging use of digital decision support tools in the study area, integration of these models with other yield-limiting and yield-reducing factors (e.g., weather, crop management) can improve yield prediction, which will enhance scenario analysis and foresight studies to optimize maize yield in the region.

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AUTHOR CONTRIBUTIONS

Bello Muhammad Shehu: Conceptualization; Data curation; Formal analysis; Methodology; Writing – original draft; Writing – review & editing. Ismail Ibrahim Garba: Investigation; Supervision; Writing – review & editing. Jibrin Mohammed Jibrin: Funding acquisition; Project administration; Resources; Supervision; Writing – review & editing. Alpha Yaya Kamara: Funding acquisition; Project administration; Resources; Writing – review & editing. Adam Muhammad Adam: Investigation; Supervision; Writing – review & editing. Peter Craufurd: Funding acquisition; Project administration; Resources; Writing – review & editing. Kamaluddin Tijjani Aliyu: Investigation; Supervision; Writing – review & editing. Jairos Rurinda: Methodology; Supervision; Visualization; Writing – review & editing. Roel Merckx: Conceptualization; Methodology; Resources; Supervision; Writing – review & editing.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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REFERENCES

Adediran, J. A., & Banjoko, V. A. (1995). Response of maize to nitrogen, phosphorus, and potassium fertilizers in the savanna zones of Nigeria. *Communications in Soil Science and Plant Analysis*, *26*(3–4), 593–606. https://doi.org/10.1080/00103629509369320

Agboola, A. A., & Ayodele, O. J. (1985). Prospects and problems of using soil testing for adoption of fertilizer use in Ekiti-Akoko Agricultural Development Project Area. In *Proceedings of Workshops on Appropriate Technologies for Farmers in Semi-Arid Africa* (pp. 123–136). Purdue University.

Aitchison, J. (1982). Statistical analysis of compositional data. *Journal of the Royal Statistical Society Series B (Methodological)*, *44*(2), 139–177.

Aitchison, J., & Egozcue, J. (2005). Compositional data analysis: Where are we and where should we be heading? *Mathematical Geology*, *37*(7), 829–850. https://doi.org/10.1007/s11004-005-7383-7

Akinyele, B. O., & Adigun, A. B. (2006). Soil texture and the phenotypic expression of maize (*Zea mays* L.). *Research Journal of Botany*, *1*, 139–143. https://doi.org/10.17311/rjb.2006.139.143

Aliyu, K. T., Huising, J., Kamara, A. Y., Jibrin, J. M., Mohammed, I. B., Nziguheba, G., Adam, A. M., & Vanlauwe, B. (2021). Understanding nutrient imbalances in maize (*Zea mays* L.) using the diagnosis and recommendation integrated system (DRIS) approach in the Maize belt of Nigeria. *Scientific Reports*, *11*(1), 16018. https://doi.org/10.1038/s41598-021-95172-7

Anderson, J. M., & Ingram, J. S. I. (1993). *Tropical soil biology and fertility: A hand book of methods* (2nd ed.). CABI International.

Arnon, D. I., & Stout, P. R. (1939). The essentiality of certain elements in minute quantity for plants with special reference in copper. *Plant Physiology*, *14*, 371–375.

Ayanlade, A. (2009). Seasonal rainfall variability in Guinea Savanna part of Nigeria: A GIS approach. *International Journal of Climate Change Strategies and Management*, *1*(3), 282–296. https://doi.org/10.1108/17568690910977492

Ayodele, O. J., & Omotoso, S. O. (2008). Nutrient management for maize production in soils of the Savanna zones of south-western Nigeria. *International Journal of Soil Science*, *3*(1), 20–27. https://doi.org/10.3923/ijss.2008.20.27

Badu-Apraku, B., Fakorede, M. A. B., Oyekunle, M., Yallou, G. C., Obeng-Antwi, K., Haruna, A., Usman, I. S., & Akinwale, R. O. (2015). Gains in grain yield of early maize cultivars developed during three breeding eras under multiple environments. *Crop Science*, *55*(2), 527. https://doi.org/10.2135/cropsci2013.11.0783

Barłóg, P. (2016). Diagnosis of sugar beet (*Beta vulgaris* L.) nutrient imbalance by DRIS and CND-clr methods at two stages during early growth. *Journal of Plant Nutrition*, *39*(1), 1–16. https://doi.org/10.1080/01904167.2014.964366

Bates, T. E. (1971). Factors affecting critical nutrient concentrations in plants and their evaluation: A review. *Soil Science*, *112*(2), 116–130. https://doi.org/10.1097/00010694-197108000-00005

Beah, A., Kamara, A. Y., Jibrin, J. M., Akinseye, F. M., Tofa, A. I., & Ademulegun, T. D. (2021). Simulation of the optimum planting windows for early and intermediate-maturing maize varieties in the Nigerian savannas using the APSIM model. *Frontiers in Sustainable Food Systems*, *5*, 64. https://doi.org/10.3389/fsufs.2021.624886

Bennett, J. G. (1980). Aeolian deposition and soil parent materials in northern Nigeria. *Geoderma*, *24*(3), 241–255. https://doi.org/10.1016/0016-7061(80)90027-0

Bremner, J. M. (1996). Nitrogen-total. In D. L. Sparks, et al. (Eds.), *Methods of soil analysis: Part 3. Chemical methods* (pp. 1085–1121). ASA and SSSA. https://doi.org/10.2136/sssabookser5.3.c37

Brown, P. H., Zhao, F.-J., & Dobermann, A. (2021). What is a plant nutrient? Changing definitions to advance science and innovation in plant nutrition. *Plant and Soil*, *476*, 11–23. https://doi.org/10.1007/s11104-021-05171-w

Claupein, W. (1993). Stickstoffdüngung und chemischer Pflanzenschutz in einem Dauerfeldversuch und die Ertragsgesetze von Liebig, L.iebscher, WOLLNY und MITSCHERLICH. *Journal of Agronomy and Crop Science*, *171*(2), 102–113. https://doi.org/10.1111/j.1439-037X.1993.tb00119.x

De Bauw, P., Van Asten, P., Jassogne, L., & Merckx, R. (2016). Soil fertility gradients and production constraints for coffee and banana on volcanic mountain slopes in the East African Rift: A case study of Mt. Elgon. *Agriculture, Ecosystems & Environment*, *231*, 166–175. https://doi.org/10.1016/J.AGEE.2016.06.036

Dewitte, O., Jones, A., Spaargaren, O., Breuning-Madsen, H., Brossard, M., Dampha, A., Deckers, J., Gallali, T., Hallett, S., Jones, R., Kilasara, M., Le Roux, P., Michéli, E., Montanarella, L., Thiombiano, L., Van Ranst, E., Yemefack, M., & Zougmore, R. (2013). Harmonisation of the soil map of Africa at the continental scale. *Geoderma*, *211–212*, 138–153. https://doi.org/10.1016/j.geoderma.2013.07.007

Ekeleme, F., Jibrin, J. M., Kamara, A. Y., Oluoch, M., Samndi, A. M., & Fagge, A. A. (2014). Assessment of the relationship between soil properties, *Striga hermonthica* infestation and the on-farm yields of maize in the dry Savannas of Nigeria. *Crop Protection*, *66*, 90–97. https://doi.org/10.1016/j.cropro.2014.09.001

ESU, I. E. (1991). *Detailed Soil Survey of NIHORT Farm at Bunkure Kano State, Nigeria*. Institute for Agricultural Reserach, Ahmadu Bello University Zaria.

Eteng, U. E., Asawalam, D. O., & Ano, O. A. (2014). Effect of Cu and Zn on maize (*Zea mays* L.) yield and nutrient uptake in coastal plain sand derived soils of southeastern Nigeria. *Open Journal of Soil Science, July*, 235–245. https://doi.org/10.4236/ojss.2014.47026

Fageria, N. K., & Oliveira, J. P. (2014). Nitrogen, phosphorus and potassium interactions in upland rice. *Journal of Plant Nutrition*, *37*(10), 1586–1600.

Fageria, V. D. (2001). Nutrient interactions in crop plants. *Journal of Plant Nutrition*, *24*(8), 1269–1290. https://doi.org/10.1081/PLN-100106981

Fakorede, M. A. B., & Akinyemiyu, O. A. (2003). Climatic change: Effects on maize production in a tropical rainforest location. In B. Badu-Apraku, M. A. B. Fakorede, M. Ouedraogo, R. J. Carsky, & A. Menkir (Eds.), *Maize revolution in West and Central Africa*. Proceedings of Regional Maize Workshop (pp. 272–282). West and Central Africa Collaborative Maize Research Network/International Institute of Tropical Agriculuture.

FAO. (2017). *The future of food and agriculture: Trends and challenges*. In *The future of food and agriculture: Trends and challenges*. FAO. https://www.fao.org/3/i6583e/i6583e.pdf

FAOSTAT. (2021). *Nigeria's agricultural profile (crops and livestock products)*. FAO. https://www.fao.org/faostat/en/#data/QCL

Farshid, A. (2012). Manganese, iron and copper contents in leaves of maize plants (*Zea mays* L.) grown with different boron and zinc micronutrients. *African Journal of Biotechnology*, *11*(4), 896–903. https://doi.org/10.5897/ajb11.165

Foster, A. F. (2001). Nutrient deficiencies and toxicities of plants CD-ROM. *Crop Science*, *41*, 917–917. https://doi.org/10.2135/cropsci2001.413917x

Friesen, D. K. (1991). Fate and efficiency of sulfur fertilizer applied to food crops in West Africa. *Fertilizer Research*, *29*, 35–44.

Gee, D. W., & Or, D. (2002). Particle-size analysis. In J. H. Dane & G. C. Topp (Eds.), *Methods of soil analysis. Part 4. Physical methods* (pp. 255–293). SSSA. https://doi.org/10.2136/sssabookser5.4.c12

Global Yield Gap Atlas (GYGA). (2021). *Maize production data, Nigeria*. GYGA. https://www.yieldgap.org/

Gott, R. M., Aquino, L. A., Clemente, J. M., Santos, L. P. D. D., Carvalho, A. M. X., & Xavier, F. O. (2017). Foliar diagnosis indexes for corn by the methods diagnosis and recommendation integrated system (DRIS) and nutritional composition (CND). *Communications in Soil Science and Plant Analysis*, *48*(1), 11–19. https://doi.org/10.1080/00103624.2016.1253714

Havlin, J. L., & Jacobsen, J. S. (1994). *Soil testing: Prospects for improving nutrient recommendations* (Vol. 40). SSSA and ASA. https://doi.org/10.2136/sssaspecpub40

Hawkesford, M. J., Schneider, A., Belcher, A. R., & Clarkson, D. T. (1995). Regulation of enzymes involved in the sulphur-assimilatory pathway. *Zeitschrift für Pflanzenernährung und Bodenkunde*, *158*, 55–57. https://doi.org/10.1002/jpln.19951580110

Heanes, D. L. (1984). Determination of total organic-C in soils by an improved chromic acid digestion and spectrophotometric procedure. *Communications in Soil Science and Plant Analysis*, *15*(10), 1191–1213. https://doi.org/10.1080/00103628409367551

Ichami, S. M., Karuku, G. N., Sila, A. M., Ayuke, F. O., & Shepherd, K. D. (2022). Spatial approach for diagnosis of yield-limiting nutrients in smallholder agroecosystem landscape using population-based farm survey data. *PLOS ONE*, *17*(2), e0262754. https://doi.org/10.1371/journal.pone.0262754

Imakumbili, M. L. E., Semu, E., Semoka, J. M. R., Abass, A., & Mkamilo, G. (2020). Plant tissue analysis as a tool for predicting fertiliser needs for low cyanogenic glucoside levels in cassava roots: An assessment of its possible use. *PLOS ONE*, *15*(2), e0228641. https://doi.org/10.1371/journal.pone.0228641

Jones Jr., J. B. (1998). *Field sampling procedure for conducting plant analysis*. CRC Press, Taylor & Francis Group.

Jones Jr., J. B. (2012). Plant nutrition and soil fertility manual *(2nd ed.)*. Taylor & Francis Group.

Jones Jr, J. B., Wolf, B., & Mills, H. A. (1991). *Plant analysis handbook; A practical sampling, preparation, analysis, and interpretation guide*. Micro-Macro Inc.

Jones, M. J., & Wild, A. (1975). Soils of West African Savanna *(Technical Communication 55). Common Wealth Bureau of Soils*.

Kamara, A. Y. (2017). Good agricultural practices for maize cultivation: The case study of West Africa. In V. Watson (Eds), *Achieving sustainable cultivation of maize, Volume 2: Cultivation techniques, pest and disease control*. Burleigh Dodds Science Publishing. https://doi.org/10.19103/AS.2016.0002.05

Kamara, A. Y., Ekeleme, F., Chikoye, D., & Omoigui, L. O. (2009). Planting date and cultivar effects on grain yield in dryland corn production. *Agronomy Journal*, *101*, 91–98. https://doi.org/10.2134/agronj2008.0090

Khiari, L., Parent, L. E., & Tremblay, N. (2001a). Selecting high-yield subpopulation for diagnosing nutrient imbalance in crops. *Agronomy Journal*, *93*, 802–808. https://doi.org/10.2134/agronj2001.934802x

Khiari, L., Parent, L. E., & Tremblay, N. (2001b). The phosphorus compositional nutrient diagnosis range for potato. *Agronomy Journal*, *93*, 815–819. https://doi.org/10.2134/agronj2001.934815x

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

Kwari, J. D., Kamara, A. Y., Ekeleme, F., & Omoigui, L. (2011). Soil fertility variability in relation to the yields of maize and soybean under intensifying cropping systems in the tropical savannas of northeastern Nigeria. In A. Bationo, B. Waswa, J. Okeyo, F. Maina, & J. Kihara (Eds.), *Innovations as key to the Green Revolution in Africa* (pp. 457–464). Springer. https://doi.org/10.1007/978-90-481-2543-2_47

Magallanes-Quintanar, R., Valdez-Cepeda, R. D., Olivares-Sáenz, E., Pérez-Veyna, O., García-Hernández, J. L., & López-Martínez, J. D. (2006). Compositional nutrient diagnosis in maize grown in a calcareous soil. *Journal of Plant Nutrition*, *29*(11), 2019–2033. https://doi.org/10.1080/01904160600928235

Malgwi, W. B., Ojanuga, A. G., Chude, V. O., Kparmwang, T., & Raji, B. A. (2000). Morphological and physical properties of some soils at Samaru, Zaria, Nigeria. *Nigerian Journal of Soil Resources*, *1*, 58–64.

Manu, A., Bationo, A., & Geiger, S. C. (1991). Fertility status of selected millet producing soils of West Africa with emphasis on phosphorus. *Soil Science*, *152*(5), 315–320. https://journals.lww.com/soilsci/Fulltext/1991/11000/fertility_status_of_selected_millet_producing.1.aspx

Marschner, P. (2012). *Mineral nutrition of higher plants* (3rd ed.). Elsevier.

Mehlich, A. (1984). Mehlich 3 soil test extractant: A modification of Mehlich 2 extractant. *Communications in Soil Science and Plant Analysis*, *15*(12), 1409–1416. https://doi.org/10.1080/00103628409367568

Møberg, J. P., & Esu, I. E. (1991). Characteristics and composition of some savanna soils in Nigeria. *Geoderma*, *48*(1–2), 113–129. https://doi.org/10.1016/0016-7061(91)90011-H

National Special Programme for Food Security (NSPFS). (2005). *Nigerian Soil Fertility Rating and Thematic Maps*. NSPFS. Federal Ministry of Agriculture.

Nelson, L. A., & Anderson, R. L. (1977). Partitioning of soil test-crop response probability. In M. Stelly (Ed.), *Soil testing: Correlating and interpreting the analytical results* (pp. 19–38). ASA.

Njoroge, R., Otinga, A. N., Okalebo, J. R., Pepela, M., & Merckx, R. (2017). Occurrence of poorly responsive soils in western Kenya and associated nutrient imbalances in maize (*Zea mays* L.). *Field Crops Research*, *210*, 162–174. https://doi.org/10.1016/j.fcr.2017.05.015

Nowaki, R. H. D., Parent, S.-É., Filho, C. A. B., Rozane, D. E., Meneses, N. B., Silva, J. A. d. S. d., Natale, W., & Parent, L. E. (2017). Phosphorus over-fertilization and nutrient misbalance of irrigated tomato crops in Brazil. *Frontiers in Plant Science*, *8*, 825. https://doi.org/10.3389/fpls.2017.00825

Nziguheba, G., Tossah, B. K., Diels, J., Franke, A. C., Aihou, K., Iwuafor, E. N. O., Nwoke, C., & Merckx, R. (2009). Assessment of nutrient deficiencies in maize in nutrient omission trials and long-term field experiments in the West African Savanna. *Plant and Soil*, *314*(1–2), 143–157. https://doi.org/10.1007/s11104-008-9714-1

Ojeniyi, S. O., & Kayode, G. O. (1993). Response of maize to copper and sulfur in tropical regions. *Journal of Agricultural Science*, *120*, 295–299. https://doi.org/10.1017/S0021859600076450

Oyinlola, E. Y., & Chude, V. O. (2010). Status of available micronutrients of the basement complex rock: Derived Alfisols in northern Nigeria savanna. *Tropical and Subtropical Agroecosystems*, *12*, 229–237.

Parent, L.-É. (2011). Diagnosis of the nutrient compositional space of fruit crops. *Revista Brasileira de Fruticultura*, *33*, 321–334.

Parent, L. E., Cambouris, A. N., & Muhawenimana, A. (1994). Multivariate diagnosis of nutrient imbalance in potato crop. *Soil Science Society American Journal*, *58*, 1432–1438. https://doi.org/10.2136/sssaj1994.03615995005800050022x

Parent, L. E., & Dafir, M. (1992). A theoretical concept of compositional nutrient diagnosis. *Journal of American Society of Horticultural Science*, *117*(2), 239–242.

Parent, L. E., Karam, A., & Visser, S. A. (1993). Compositional nutrient diagnosis of the greenhouse tomato. *Horticultural Science*, *28*(10), 1041–1042.

Parent, S.-É., Parent, L. E., Rozanne, D. E., Hernandes, A., & Natale, W. (2012). Nutrient balance as paradigm of plant and soil chemometrics. In R. N. Issaka (Ed.), *Soil fertility* (pp. 83–114). InTech. https://doi.org/10.5772/53343

Petersen, J., Thomsen, I. K., Mattsson, L., Hansen, E. M., & Christensen, B. T. (2012). Estimating the crop response to fertilizer nitrogen residues in long-continued field experiments. *Nutrient Cycling in Agroecosystems*, *93*(1), 1–12. https://doi.org/10.1007/s10705-012-9482-4

Ravensbergen, A. P. P., Chamberlin, J., Craufurd, P., Shehu, B. M., & Hijbeek, R. (2021). Adapting the QUEFTS model to predict attainable yields when training data are characterized by imperfect management. *Field Crops Research*, *266*, 108126. https://doi.org/10.1016/j.fcr.2021.108126

Reuters, D. J., & Robinson, J. B. (1997). *Plant analysis: An interpretation manual*. CSIRO.

Rietra, R. P. J. J., Heinen, M., Dimkpa, C. O., & Bindraban, P. S. (2017). Effects of nutrient antagonism and synergism on yield and fertilizer use efficiency. *Communications in Soil Science and Plant Analysis*, *48*(16), 1895–1920. https://doi.org/10.1080/00103624.2017.1407429

Roy, R. N., Finck, A., Blair, G. J., & Tandon, H. L. S. (2006). *Plant nutrition for food security*. (FAO Fertilizer and Plant Nutrition Bulletin 6). FAO.

Sahrawat, K. L. (2006). Plant nutrients: Sufficiency and requirements. In R. Lal (Ed.), *Encyclopedia of soil science* (pp. 1306–1310). CRC Press.

SAS Institute. (2017). *JMP® 13 documentation library*. SAS Institute.

Schleuss, P. M., Widdig, M., Heintz-Buschart, A., Kirkman, K., & Spohn, M. (2020). Interactions of nitrogen and phosphorus cycling promote P acquisition and explain synergistic plant-growth responses. *Ecology*, *101*(5), e03003. https://doi.org/10.1002/ecy.3003

Schulz, S., Diels, J., & Lyasse, O. (2002). Rehabilitation of severely degraded soil through the application of limiting nutrient: An example from Shika farm. In *Improving and intensifying cereal–legume systems in the moist and dry savanna of West and Central Africa* (pp. 4–5). International Institute of Tropical Agriculture.

Schut, A. G. T., & Giller, K. E. (2020). Soil-based, field-specific fertilizer recommendations are a pipe-dream. *Geoderma*, *380*, 114680. https://doi.org/10.1016/j.geoderma.2020.114680

Shehu, B. M., Lawan, B. A., Jibrin, J. M., Kamara, A. Y., Mohammed, I. B., Rurinda, J., Zingore, S., Craufurd, P., Vanlauwe, B., Adam, A. M., & Merckx, R. (2019). Balanced nutrient requirements for maize in the northern Nigerian Savanna: Parameterization and validation of QUEFTS model. *Field Crops Research*, *241*, 107585. https://doi.org/10.1016/j.fcr.2019.107585

Shehu, B. M., Merckx, R., Jibrin, J. M., Kamara, A. Y., & Rurinda, J. (2018). Quantifying variability in maize yield response to nutrient applications in the northern Nigerian savanna. *Agronomy*, *8*(2). https://doi.org/10.3390/agronomy8020018

Sileshi, G., Akinnifesi, F. K., Debusho, L. K., Beedy, T., Ajayi, O. C., & Mong'omba, S. (2010). Variation in maize yield gaps with plant nutrient inputs, soil type and climate across sub-Saharan Africa. *Field Crops Research*, *116*(1–2), 1–13. https://doi.org/10.1016/J.FCR.2009.11.014

Sillanpää, M. (1982). *Micronutrients and the nutrient status of soils: A global study* (Soils Bulletin 48). FAO.

Sinclair, A. G., Morrison, J. D., Smith, L. C., & Dodds, K. G. (1997). Determination of optimum nutrient element ratios in plant tissue. *Journal of Plant Nutrition*, *20*(9), 1069–1083. https://doi.org/10.1080/01904169709365319

Smaling, E. M. A., Nandwa, S. M., & Janssen, B. H. (1991). Soil fertility in Africa is at stake. In R. J. Buresh, P. A. Sanchez, & F. Calhoun

(Eds.), *Replenishing soil fertility in Africa* (Vol. 51, pp. 47–61). SSSA and ASA. https://doi.org/10.2136/sssaspecpub51.c2

Swets, J. A. (1988). Measuring the accuracy of diagnostic systems. *Science*, *240*(4857), 1285–1293. https://doi.org/10.1126/science.3287615

Tabi, O. T., Diels, J., Ogunkunle, A. O., Iwuafor, E. N. O., Vanlauwe, B., & Saginga, N. (2008). Potential nutrient supply, nutrient utilization efficiencies, fertilizer recovery rates and maize yield in northern Nigeria. *Nutrient Cycling in Agroecosystems*, *80*, 161–172. https://doi.org/10.1007/s10705-007-9129-z

Walworth, J. L., & Sumner, M. E. (1987). *The diagnosis and recommendation integrated system (DRIS)*. In B. A. Stewart (Ed.), *Advances in soil science* (Vol. 6, pp. 149–188). Springer. https://doi.org/10.1007/978-1-4612-4682-4_4

Ware, G. O., Ohki, K., & Moon, L. C. (1982). The Mitscherlich plant growth model for determining critical nutrient deficiency levels. *Agronomy Journal*, *74*, 88–91. https://doi.org/10.2134/agronj1982.00021962007400010024x

Zhao, F. J., Bilsborrow, P. E., Evans, E. J., & McGrath, S. P. (1997). Nitrogen to sulphur ratio in rapeseed and in rapeseed protein and its use in diagnosing sulphur deficiency. *Journal of Plant Nutrition*, *20*(4–5), 549–558. https://doi.org/10.1080/01904169709365273

SUPPORTING INFORMATION

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