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Diagnosis of Soil Nutrient Constraints in Small-Scale Groundnut (*Arachis hyopaea* L.) Production Systems of Western Kenya Using Infrared Spectroscopy

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Abstract: Wise decision-making on resource allocation and intervention targeting for soil management cannot rely solely on trial and error methods and field observations used by small-scale farmers: cost-effective soil fertility survey methods are needed. This study aimed to test the applicability of infrared spectroscopy (IR) as a diagnostic screening tool for making soil fertility recommendations in small-scale production systems. Soil fertility survey of 150 small-scale groundnut farms in western Kenya was conducted using a spatially stratified random sampling strategy. Soil properties examined were pH in water (pH_w), total carbon (C), total nitrogen (N), extractable phosphorus (P), exchangeable potassium (K), calcium (Ca), magnesium (Mg) and texture. These properties were calibrated to mid-infrared (MIR) diffuse reflectance using partial least square regression (PLSR). Cross-validated coefficient of determination (r^2) values obtained from calibration models were > 0.80 for all properties, except P and K with 0.66 and 0.50 respectively. Soil nutritional deficiencies were evaluated using critical nutrient limits based on IR predictions and composite soil fertility indices (SFIs) developed from the soil properties using principal component analysis. The SFIs were calibrated to MIR soil spectral reflectance with cross-validated r^2 values > 0.80. The survey showed that 56% of the groundnut farms had severe soil nutrient constraints for production, especially exchangeable Ca, available P and organic matter. IR can provide a robust tool for farm soil fertility assessment and recommendation systems when backed up by conventional reference analyses. However, further work is required to test direct calibration of crop responses to spectral indicators and to improve prediction of extractable P and K tests.

Key words: Infrared spectroscopy, nutrient constraints, small-scale farmers, soil fertility indices, groundnut.

1. Introduction

Soil fertility degradation is a major biophysical cause of food insecurity, and a major driving factor leading to abject poverty in sub-Saharan Africa (SSA) [1]. Human-induced soil degradation is reported to have affected 15% of global land area [2] and 65% of Africa arable soils [3]. Western Kenya supports one of the densest rural agricultural populations in the world as a result of large initial settlements attracted by the originally fertile soils in the area [4]. However, population growth and continuous, low input cropping has led to steadily declining soil fertility in the area [4, 5].

Decline of groundnut yields on small-scale farms of western Kenya has been attributed to soil fertility degradation as one of the main factors [6, 7]. Groundnut is an important food, feed and cash crop in many countries in SSA. Africa accounts for 40% of the world groundnut area but produces only 25% of

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world total because yields are low [8, 9]. The grain legume crop contributes to food security and soil fertility replenishment through biological nitrogen fixation. Contributions of groundnuts to nutrient replenishment through biological nitrogen fixation, has been estimated using nitrogen isotope (N^{15}) data, as about 40 kg N ha^{-1}[10]. In most SSA countries, women predominantly grow and manage groundnuts hence groundnut cultivation has a direct bearing on the overall economic, nutritional and livelihood of women and children.

The small-scale groundnut farming systems are characterized by low use of mineral fertilizers and poor soil fertility management systems, leading to declining crop yields [11]. Nutrient depletion on the farms is due to crop harvests, removal of crop residues, leaching, erosion and lack of soil sufficient nutrient replenishment [4, 12, 13]. Knowledge on nutrient constraints in groundnut production systems is limited compared to staple crop production (such as maize) in Western Kenya [6]. The knowledge on nutrient depletion, dynamics and management on small-scale groundnut farms is an important pre-requisite for designing integrated approaches for effective and sustainable soil nutrients management in small-scale production systems [14].

In SSA, national soil fertility monitoring systems are insufficient, in part, due to high costs and labour demands for conventional soil diagnosis based on wet chemistry methods [12]. According to existing farming practice, small-scale farmers often lack information and have limited access to information on integrated nutrient management approaches that are based on empirical evidence of nutrient constraints. As a result, farmers use trial and error methods, and indigenous knowledge systems as diagnostic tools [15]. This is often not enough as a decision support in small-scale farming, which requires detailed information on soil nutrient management as well as integrated soil fertility management options [5, 13]. However, the diagnosis of soil nutritional constraints requires soil analysis by conventional laboratory wet chemistry methods and these services are expensive for large-scale application by national soil survey and small-scale farmers. There is need for inexpensive and rapid analytical methods.

Establishment of rapid, reliable and low cost analytical tools and techniques for assessing soil nutritional constraints has been identified as a priority for African governments in a review commissioned by a New Partnership for Africa Development (NEPAD) [16]. Infrared (IR) spectroscopy has attracted interest among soil scientists as a possible technique for improved soil analyses, providing rapid, non-destructive, cheap measurements as well as possibilities to determine several soil properties simultaneously [17-19]. Infrared (IR) spectroscopy analysis is based on the interaction of IR light with matter. Infrared is part of the electromagnetic spectrum and its divided into three main regions according to wavelength; near infrared (NIR) 12,500-4,000 cm^{-1}, mid-infrared (MIR) 4,000-400 cm^{-1} and far infrared less than 400 cm^{-1}. The characteristic of IR light gives distinctive properties that correlate uniquely with properties of matter [20]. The shape of IR spectra responds to organic matter, mineralogy, and particle size distribution, which also principally determine soil fertility status.

A number of studies have shown the potential of NIR to predict soil texture [21-24] as well as soil organic carbon (C) [22, 24-26]. Other soil properties such as plant mineral nutrients and pH have been estimated with NIR in a number of studies with promising, though varying, results [17, 27-30]. NIR has also been related to potentially mineralisable N derived from aerobic and anaerobic incubations [22, 23, 31-33] and has been used with promising results to estimate N uptake in crops [33-35]. Shepherd and Walsh [21] proposed an IR approach based on building soil spectral libraries and illustrated the approach for African soils. Recent development include, a new NIR sensing device that is able to

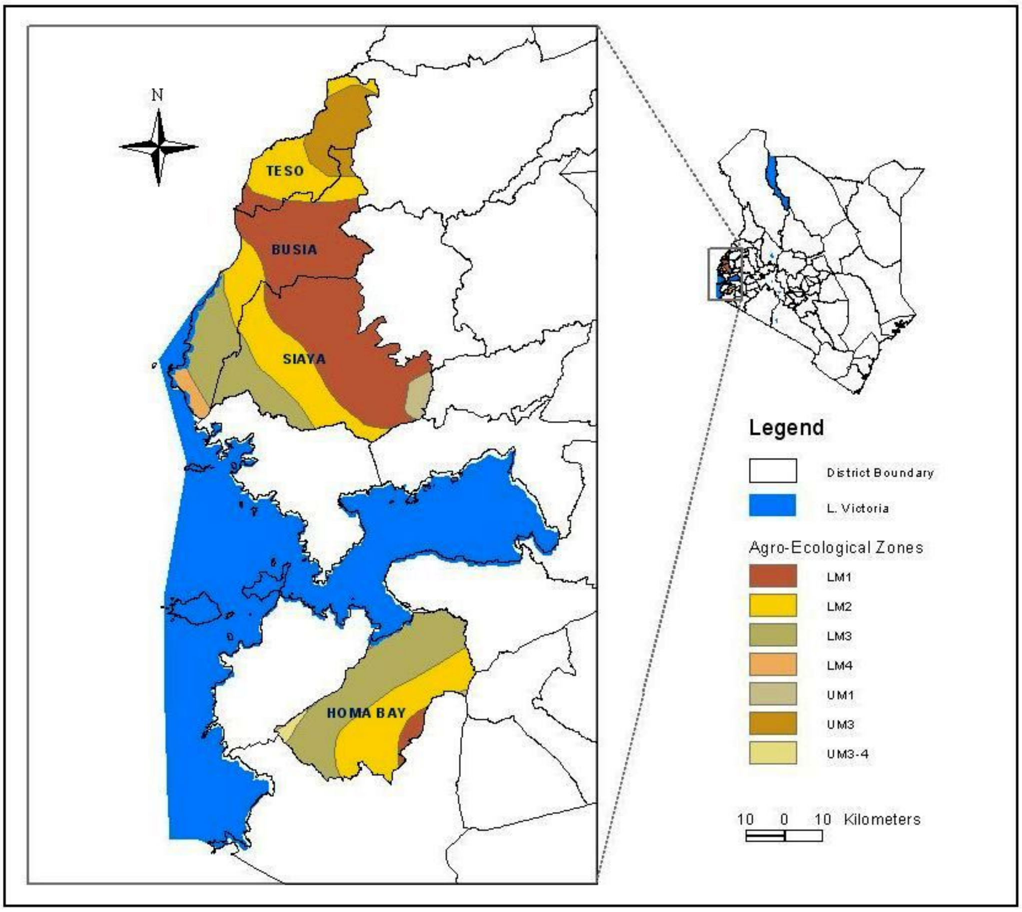

Fig. 1 Agro-ecological zones for the study area.

collect *in situ* 3D spectral data of an entire soil profile, allowing objective and rapid soil classification [36]. Linker et al. [37] was able to determine nitrates from soil pastes using attenuated total reflectance (ATR) spectroscopy in the MIR spectral region. MIR is energetic enough to excite molecular vibrations to higher energy levels than NIR [38].

Although several workers have demonstrated the effectiveness of IR for characterization and determining soil properties [39-41] limited studies have demonstrated the applicability of IR as a soil nutrient diagnostic tool. The use of IR in soil applications remains poorly developed [40]. Many studies have focused on the prediction of soil properties through the processes of calibration and validation, centering the interest on simplifying soil analysis compared to the laborious and costly traditional chemical methods.

The potential of IR as a technique that can be applied as a simple and rapid diagnostic tool for soil nutrient assessment and monitoring in small-scale farming systems has not been fully exploited. Therefore, this study sought to: (1) explore the applicability of IR as a soil nutrient diagnostic tool in smallholder farm surveys and (2) demonstrate its use in assessing the prevalence of soil nutrient deficiencies in small-scale groundnut production systems of western Kenya.

2. Materials and Methods

2.1 Study Area and Site Selection

The study was conducted in Busia, Teso, Siaya, Homa Bay and Suba districts in western Kenya, characterized by low agricultural productivity (Fig. 1). The districts cover a wide range of distinct soil and climatic characteristics, with agro-ecological zones (AEZ) ranging from, the Upper Midland 4 Coffee and Maize Zone (UM_4), the Lower Midland (LM_1) Sugarcane Zone and the drier Cotton/Sorghum/Sunflower Lower Midlands (LM_3 to LM_4) [42]. Western Kenya has diverse soil types with dominant soils including humic gleysols dominating the lower regions, with ferralo-orthic ferralsols, orthic acrisols and chromic luvisols most common in the higher altitude areas [42, 43]. The soils are generally poor with phosphorus as the main limiting macronutrient [1]. The farming system is typically dominated by intensive small-scale production enterprises, characterized by poor soil fertility and high poverty levels.

2.2 Sample Collection and Analysis

A random sample of 150 farms was taken from a list of 600 groundnut growers across five districts spanning agro-ecological zones (AEZ) LM_1, LM_2, LM_3, LM_4, and UM_4. Soil sampling was conducted using a zigzag scheme on each groundnut field, where by five points per acre were considered appropriate, as described by Okalebo et al. [44]. From each sampling point a soil sample was extracted using an Edelman soil auger at 0 to 20 cm depth. The five soil samples from each field were composited for soil nutrient analysis. Prior to nutrient analysis, soils were air-dried and ground to pass through a 2 mm sieve.

2.3 Spectral Measurements

Diffuse MIR reflectance spectra (4,000-600 cm^{-1}) were determined on the air-dried soil samples, after fine grinding, using a Bruker High-Throughput-Screening (HTS-XT) accessory attached to a Bruker Tensor 27 FT-IR spectrometer. Approximately 0.03 grams of soil were loaded into wells in aluminum micro-plates with four replicate wells per soil sample (Fig. 2) to enable MIR spectral measurement. An empty well was used for reference readings, taken before each sample reading using an

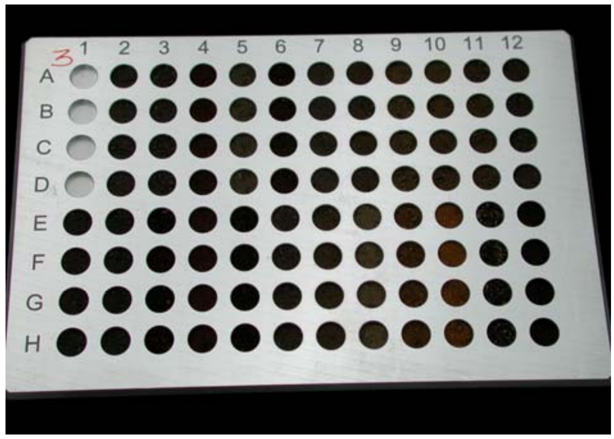

Fig. 2 Aluminum micro plate used to scan ground soil samples.

average of 32 scans. Absorbance was recorded at a spectral resolution of 4 cm^{-1} zero-filled to 2 cm^{-1}. First derivative spectra with a smoothing gap of 3 points were used in all the analysis.

2.4 Development of Soil Reference Data

One hundred soil samples (25% of the original soil samples) were selected for reference chemical analysis. Spectra were ranked according to the Euclidean distance of the principal component space and 25 samples were randomly selected from each of the quartiles, giving 100 samples in total. Chemical analyses were conducted using standard laboratory methods as reported by Shepherd and Walsh [22], for development of calibration models. Soil pH_w was determined using an electrode pH meter from a saturated soil paste using a 1:2.5 soil/water ratio. Exchangeable calcium and magnesium were determined by extraction with 1 M KCl using a 1:10 soil/solution ratio using an atomic absorption spectrometer (ASS) [45, 46]. The Olsen method (pH 8.5, modified Olsen) was used to determine extractable phosphorus (P) using molybdate reaction for colorimetric detection with a flame emission spectrometer [45, 46]. Total carbon (C) and total nitrogen (N) were determined by the dry combustion technique using a CN analyzer [47]. Soil particle size distribution was determined using the Bouyoucos hydrometer method following Gee and Bauder [48].

2.5 Calibration Models

Chemical reference values were calibrated to the smoothed first derivative spectra using partial least square regression (PLSR) [19, 22, 23]. OPUS software version 6.5 (Bruker Inc) was used for the calibrations. Soil reference data was log transformed to achieve a normal distribution. The reliability and robustness of the calibration model was evaluated by the hold-out cross-validation procedure, using the coefficient of determination (r^2) and the root mean square error of cross validation (RMSECV) calculated using the following equations [49-51].

$$r^2 = \frac{SSR}{TSS} \qquad (1)$$

$$RMSECV = \sqrt{\sum_{i=1}^{N_p} \frac{(\hat{y}_{CV,i} - y_i)^2}{N_p}} \qquad (2)$$

Where *SSR* is the sum square of regression, and *TSS* is the total sum of squares, $\hat{y}_{CV,\ i}$ and y_i are the predicted and measured reference values respectively and N_p is the number of samples tested. The default routine for automatic outlier detection in OPUS was used to omit outliers from the calibrations. This routine identifies outliers as samples whose predicted values significantly deviate from the reference wet chemistry values using an F-test (99% probability). The resulting calibration model was used to estimate (predict) the soil properties for all soil samples falling within the property domain of the calibration set.

2.6 Development of Composite Soil Fertility Indices

Soil properties are often inter-correlated and as a result, co-variation in soil properties was analyzed statistically through principal component analysis (PCA) using the Unscrambler software (Version 9.2). Principal component analysis (PCA) is a multivariate analysis in which data reduction is applied to develop new composite variables called principal components (PC) as a result of a linear combination of original independent variables [52]. The first few components typically explain most of the variation in the entire original data set and their loadings show the contributions of the soil variables to each PC. The soil variables were standardized by dividing each observation by its standard deviation for the variable so that all variables had an equal opportunity to influence the model regardless of the range in the data [49]. Hence the component scores are in standard deviation units above or below the model centre. The principal components were examined for their usefulness as composite soil fertility indicators (SFI). Assessment of the potential soil nutrient constraints was further assessed based on critical concentrations levels defined as the concentration that separates the zone of deficiency from the zone of adequacy [44].

3. Results and Discussion

3.1 Calibration and Validation Models

Fig. 3 presents results of the IR calibration models in the MIR spectral region. Calibration models developed for pH_w, C, N, Ca, Mg, clay, sand and silt gave good fits with cross-validated r^2 values > 0.80. Models with highest r^2 and lowest RMSECV are considered to be statistically the best and robust [50]. Numerous researchers have reported accurate predictions of C [53] and soil pH [22, 23, 29, 35]. This is consistent, considering that numerous bonds between C and O, N or H absorb light in this region while pH absorption has been attributed to O-H groups [53]. The good predictions of soil texture are consistent with previous studies that have yielded good results especially clay content [54-56]. Particle size effect on light transmission and reflection explain the accurate prediction for texture [55].

Only fair calibration was obtained with extractable P (r^2 = 0.66) and were comparable to previous research findings form air-dried soil samples [54] but were better compared to those reported by Janik et al. [39] with r^2value of 0.07 for extractable P. Good predictions are less frequent for soil P and exchangeable K as well as mineral N [54]. Daniel et al. [57] reported moderate results with r^2 = 0.81 from air- dried soils for extractable P. However, Maleki et al. [58], reported

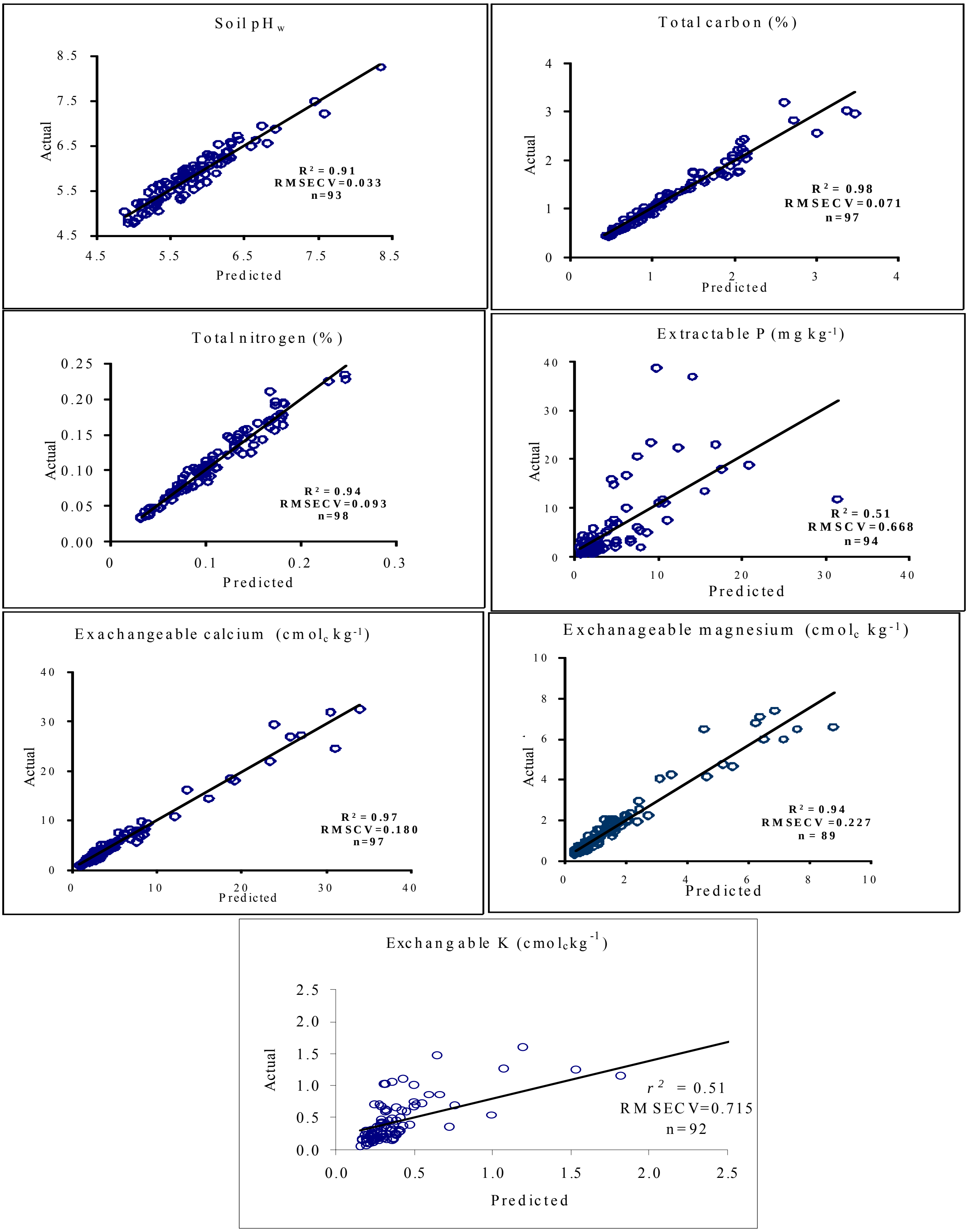

Fig. 3 Cross-validated calibration models for principal soil nutrients: soil pH$_w$, total carbon, total nitrogen, extractable phosphorus, and exchangeable calcium, magnesium and potassium.

better results (r^2 = 0.88) for *in situ* spectral measurement of P from fresh wet soils. The goodness of fit probably depends on the strength of the relation of extractable P on soil mineralogy and organic matter, which largely determine spectral shape. The prediction of exchangeable K was low (r^2 value of 0.51) but comparable to reported values [21].

Contradictory and often poor prediction results for extractable P and exchangeable K may have several causes, either relating to the reference methods (e.g., prediction of the cations varies with the extraction method [23], the nature of the study element (e.g., spectrally distinct P-containing compounds may variably contribute to soil P content [54]), its concentration (below the detection limits), or possible interaction with other components such iron oxides [54]. Increases in extractable P resulting from recent fertilizer additions would not affect soil mineralogy and organic matter and may thus not be spectrally detectable. The poor prediction could also be due to the soil test not relating well to soil P supply, in which case the efficacy of the soil test may still be in question. However, this can be validated through crop response trials.

3.2 Characterization of Soil Nutrient Status in Groundnut Farms

Fig. 4 represents box plots for predicted soil nutrient levels using MIR data in different agro-ecological zones with the critical limit levels as well as the optimum levels for soil pH_w. There were significant differences (*$P < 0.01$*) between mean soil pH_w values across the AEZs. There was far more variation within than between the AEZs.

3.2.1 Soil pH_w

Soil pH_w in the groundnut farms was within the recommended range (5.3-7.3) for optimum groundnut yields [59]. Soil pH is important as a soil fertility variable in groundnut production. Seventy nine percent of the farms had the soil pH_w within the recommend range in all AEZs. Fifteen percent of the sampled groundnut farms in LM_3 had high soil pH value > 7.3.

Studies have shown that low soil pH significantly influences groundnut seedling survival and early growth stages [60]. Low soil pH (below 5.2) affects availability of P and molybdenum, which are important for early root development for legume crops such as groundnut [61]. Low soil pH results in high concentration of hydrogen ions (H^+) in the soil that induce root injury and change the root membrane permeability and interferes with absorption and transport of both water and nutrients [61] of groundnut crops. Therefore low pH negatively affects groundnut growth that eventually leads to low yields. In particular, low soil pH, below about 5.3, is linked to aluminum toxicity [1]. One third of tropical soils have strong acidity with soluble aluminum levels that are toxic to most crop species [1]. The availability of exchangeable bases (Ca, Mg and K) is sub-optimal at low pH [62, 63, 65, 66]. Calcium is essential for proper groundnut pod development and production of high quality seed [62-66]. Lack of these essential basic cations could result to low groundnut yields. However, in these farms low soil pH was not a significant problem.

3.2.2 Total Carbon

Thirty percent of the groundnut farms had C concentration levels above the critical concentration level of 2%. Critical limits for nutrient supply and soil structure maintenance are expected to vary with soil texture and mineralogy. The agronomic limit for concentration of C recommended in Kenya for cultivated farms is 2% [44, 67] Universally, C is considered an important indicator of soil fertility as it plays a key role in nutrient availability and structure of soil. Therefore, low C concentration can indicate poor soil fertility and advanced land degradation [1]. However, threshold levels will vary with texture and mineralogy and there is need for development of local reference values.

Traditionally, natural fallow was one of the

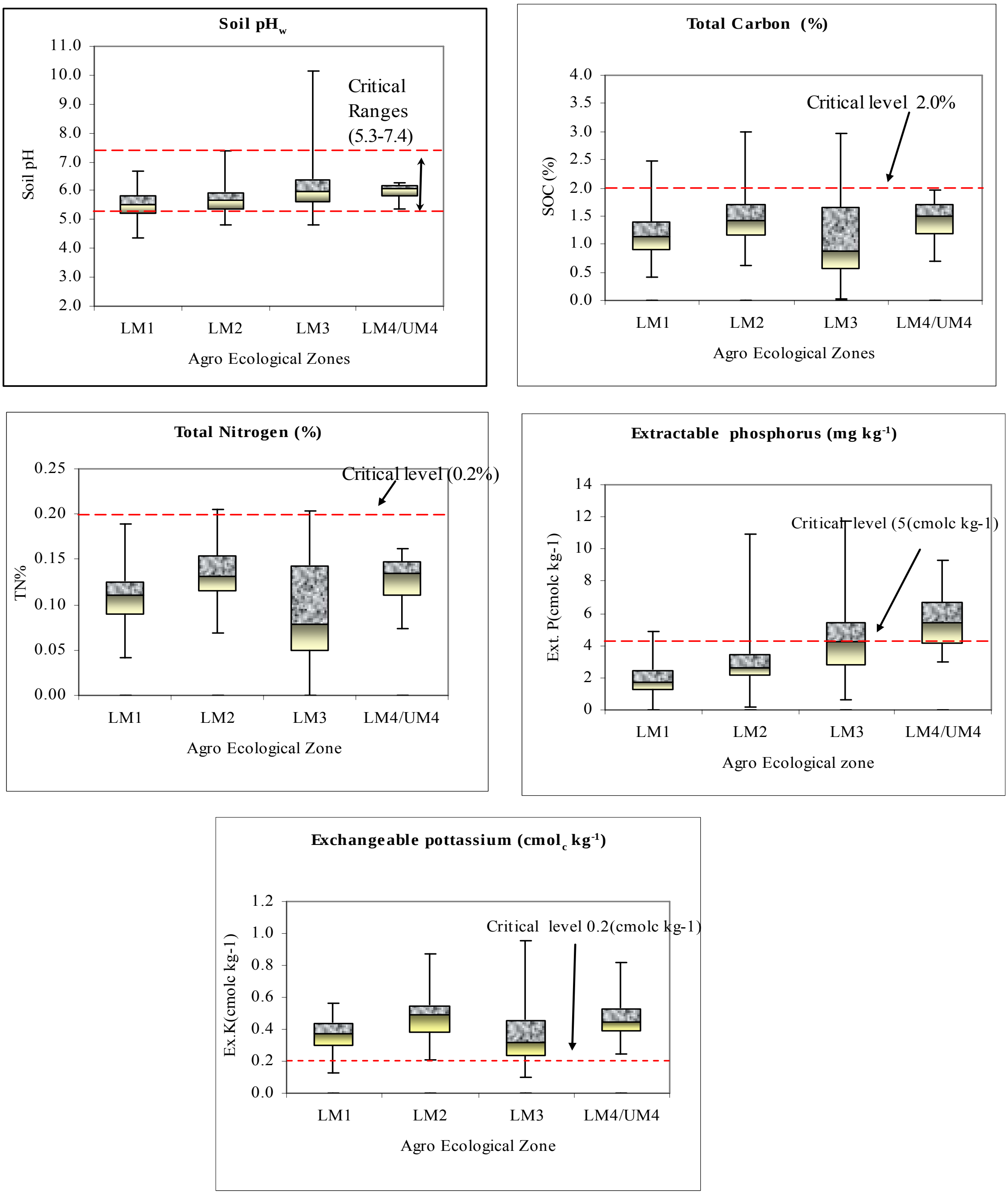

Fig. 4 Box plots indicating distribution of soil fertility parameters in small-scale groundnut farms in Western Kenya.

strategies for improving soil carbon and is still practiced even in this densely populated region, although land allocated to it is typically less than 10% of the cultivated area [68]. Its effectiveness in improving crop yields is, however, limited by the short duration (typically less than 1 year) of the practice in this densely populated area. Poorly responsive infertile soils require long term rehabilitation of soil carbon to build up soil fertility before crops respond to ensure efficient use of applied soil nutrients [69]. Farmyard manure is a common input, but its potential to meet the soil carbon stocks for effective soil fertility is limited because it is usually not available in sufficient quantities on most small-scale farms, and it's processing and application is labour demanding [69-71]. Additionally, crop residues that could be used for soil fertility improvement often have competing uses such as fodder for livestock or are used as fuel wood [72].

3.2.3 Macronutrients-Nitrogen, Phosphorus, Potassium

There was no significant difference across the AEZs in the mean N concentration levels. The LM_1 and LM_2 zones had similar mean nitrogen concentration levels of TN 0.11% while LM_3 had the lowest at 0.10% and LM_4/UM_4 had highest at 0.15%. Mean TN concentration was lower than the recommended critical limit value of 0.2% [44] in 75% of the sampled groundnut farms. The results indicate widespread limitation of N on groundnut farms.

Nitrogen is not regarded as a major constraint for groundnut production due to the crop's capacity to fix atmospheric nitrogen (N_2) [73]. This is because, when inoculated with effective strains of *Rhizobia*, enough N is fixed through symbiotic relations with *Brayrhizobium* spp. [73]. However, in practice most researchers have reported that N fertilization is required for optimum groundnut yields in N deficient soils [64]. Nitrogen is important when plant demand is high in early stages of groundnut growth before nitrogen fixation has not yet started [74]. Uptake of nitrogen is most intensive during reproductive stages of groundnuts and immobilization of N from leaves to developing fruits occurs during this stage [73, 75].

Extractable P and exchangeable K varied widely across the AEZs. The levels of extractable P was below the critical level of 5.0 mg kg^{-1} for grain legume crops [44] in 67% of the sampled groundnut farms. The average extractable P levels in LM_1, LM_2 and LM_3 were 3.1, 3.8, and 4.0 mg kg^{-1}.These results conform to previous reports that P is a major limiting soil nutrient in western Kenya [72, 76, 77]. The limitation of P availability can be due to high fixation of P of aluminum and iron oxides in tropical soils [1, 78]. Groundnuts preferably are grown on sandy soils with low amounts of clay, and phosphorus fixation in generally is not a problem [66, 78, 79]. Groundnuts have P-solubilising substances within cell walls that enable them to absorb iron-bound P in low-P soils [80], rendering this crop potentially more adapted to soils with low P. Cox et al. [66] observed that in most parts of the world groundnuts are grown in sandy soils that are deficient in phosphorus. However, these soils had a wide textural range with widespread P- deficiency.

The exchangeable potassium was above the critical recommended limit of 0.2 $cmol_c$ kg^{-1} levels [44] and deficiency was detected in only 15% of the farms. Potassium is important for groundnut growth as it provides resistance to insect pests, diseases, water stress and promotes economic water utilization [66]. However, scientific findings have indicated that groundnut requires very little K for its growth and reproduction [60]. This is because groundnut roots are efficient in obtaining K from low available levels in soil due to the presence of solubilising substances within the root cell wall [80, 81]. There is need to locally refine critical soil test limits in relation to crop responses to applied K.

3.3 Variation of Soil Nutritional Properties

Principal component analysis (PCA) provided a holistic representation of variation in soil properties, taking into account correlations among soil properties [82]. Fig. 5 presents a principal component loading plots for the eight soil nutrients. The first and second principal component (PC1 and PC2) explained 74% of total variation for the soil nutrient data. Fifty percent of the total variance was explained by PC1 which was strongly influenced by C, N, Ca, Mg and particle size distribution, with P, K and pH having the least influence. The second principal component (PC 2) explained 23% of total variance and was most strongly influenced by P and $pH_{w,}$ and to a lesser degree, K.

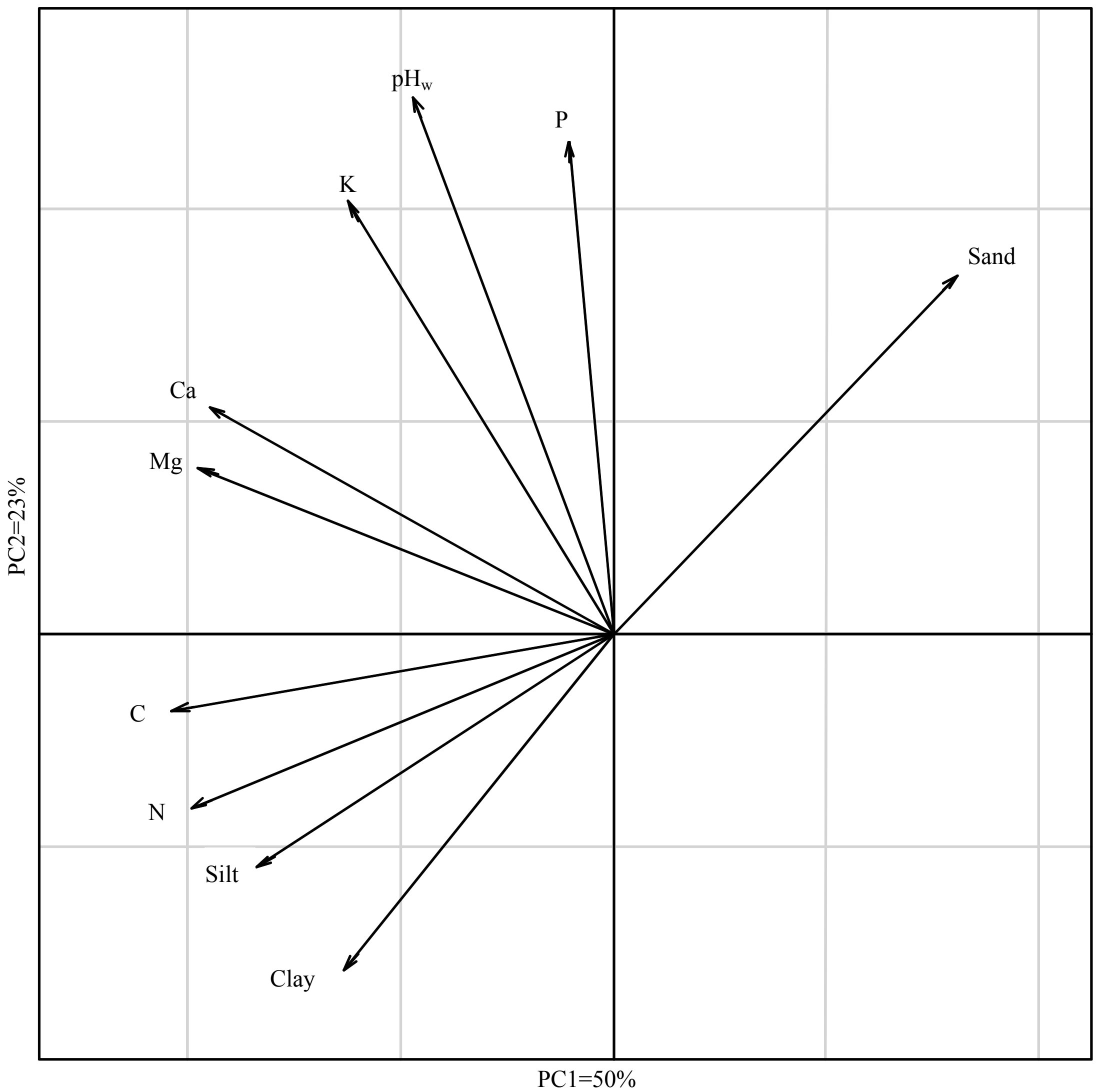

Fig. 5 Principle component analysis (PCA) loading plot for soil variables.

3.4 Soil Fertility Index and Its Interpretation for Assessment of Soil Nutrient Prevalence

The first two PCs relate to soil functions that are important for groundnut and general crop production. PC1 and PC2 were thus renamed as soil fertility index (SFI), SFI_1 and SFI_2 respectively, with SFI_1 taken to reflect basic soil fertility and SFI_2 to reflect P availability and its pH dependence. The advantage of synthesizing several soil fertility variables into one indicator, apart from simplicity, is the inter-correlation among the variables is utilized to provide more robust predictions than if they are treated individually. The index rating system used here relies on statistical approach, which yields the relative assessment of soil fertility in small-scale groundnut farms. This index combines the quality control approach described by Larson and Pierce (1994) [82] and with scoring function approach of Karlen and Stott (1994) [83].

Fig. 6 shows the relationships between soil properties and the SFIs. The concentration of principal soil nutrient increases in a non-linear way as one move from a negative fertility score to positive values. The non-linear trend is useful because it is helps to distinguish sites that have high nutrient levels and that are not in need of amelioration from those that most probably do need amelioration.

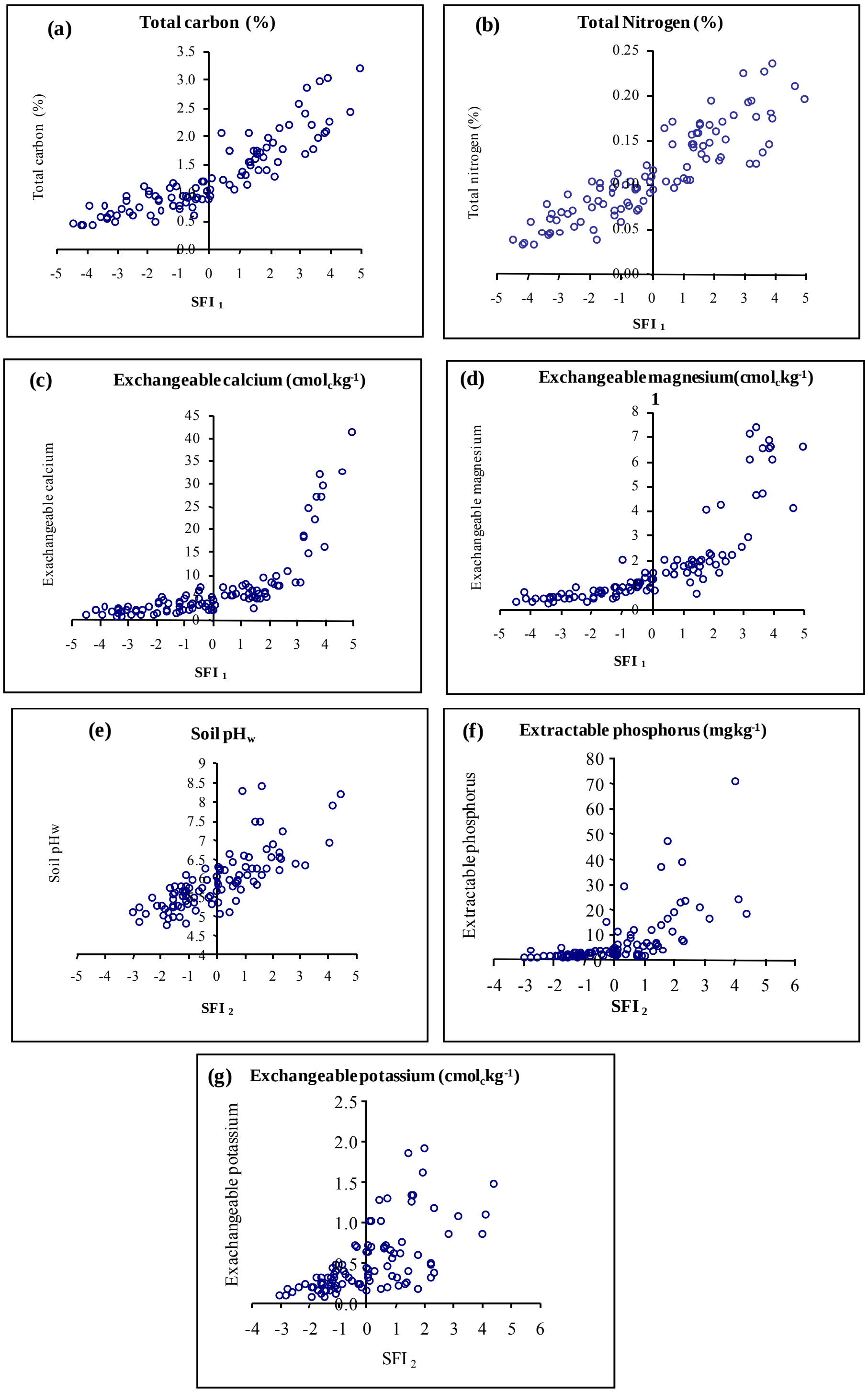

Fig. 6 Plots of soil fertility variables against soil fertility indicators, SFI_1 and SFI_2.

3.4.1 Interpretation of SFI_1

An interpretation guide to the soil fertility indicators based on mean concentration value is shown in Tables 1 and 2.

A guide on the interpretation of soil fertility scores based on SFI_1 is given below presented in Table 1.

When SFI_1 value is -2 or below, (i.e. more than two standard deviations below the average) C, P, N, K and Ca levels are at very low levels. Although the following associations with SFI_1 were weak, there was

Table 1 Interpretation of SFI_1 in terms of mean values of soil nutrient concentrations, expressed in normal units for ease of interpretation.

SFI_1	Soil pH (units)	C (%)	N (%)	Ca ($cmol_c\ kg^{-1}$)	Mg ($cmol_c\ kg^{-1}$)	P (mg/kg)	K ($cmol_c\ kg^{-1}$)	Sand (%)
-5	5.40	0.18	0.03	0.71	0.01	0.00	0.10	16
-2	5.70	0.61	0.08	0.83	0.50	0.97	0.18	29
0	5.80	1.27	0.11	6.23	1.52	3.52	0.42	47
2	6.70	1.93	0.16	9.64	2.30	4.70	0.55	59
5	7.30	2.90	0.20	21.39	4.09	10.15	0.83	70

Table 2 Interpretation of SFI_2 with pH and concentration of extractable soil nutrients, expressed in normal units for ease of interpretation.

SFI_2	Soil pH (units)	P (mg/kg)	K ($cmol_c\ kg^{-1}$)
-3	5.0	0.45	0.10
-2	5.2	1.50	0.23
0	6.0	4.19	0.43
2	6.5	10.93	0.60
3	7.2	15.70	0.85

also a tendency at $SFI_1 < -2$ for moderate acidity (< 5.7), extremely deficient P levels (< 1 mg kg^{-1}) and exchangeable K levels in the deficient range (< 0.2 $cmol_c\ kg^{-1}$). Exchangeable Ca levels below 4.0 $cmol_c\ kg^{-1}$ are generally considered to be critically low in tropical soils. These soils will need major rehabilitation for good groundnut production. 39% of the sampled groundnut farms fell in this category.

When SFI_1 falls below a value of 2, available phosphorus becomes deficient for groundnut production ($P < 5$ mg kg^{-1}). This reflects the effect of soil texture, organic matter and acidity on the availability of phosphorus. Between -2 and 2, P-replenishment is required with only maintenance dressings of K. Above 2, soils have good potential for groundnut production and only maintenance dressings of P and K may be required. However the associations of P and K with SFI_1 were weak and it is better to examine SFI_2 for confirmation of these limitations. Organic matter levels may also need to be maintained.

When SFI_1 value is 5 and above, C (2.90%), N (0.20%) and K (0.83 $cmol_c\ kg^{-1}$) are on average above the critical recommended levels and the soil pH (7.3) is near neutral and within the optimum range for groundnut productivity. 41% of farms fell in this category.

3.4.2 Interpretation of SFI_2

Table 2 shows an interpretation a soil fertility scores based on SFI_2 values. An interpretation guide is given below:

When the score for SFI_2 is -3 or lower P, pH_w and K are sub-optimal. There is an indication of acid infertility (pH < 5.0) with extractable P being very deficient (0.45 mg kg^{-1}) as well as K levels below the critical level of 0.2%. The prevalence of groundnut farms that fell within this fertility score of 2 and -3 were 35% and would need a major soil nutrient replenishment programme (e.g. liming programme) for improved groundnut yields.

Extractable P becomes moderate when SFI_2 score is above 0 with a mean value of 5.2 mg kg^{-1} at 4, which is about the critical recommended level (5.0 mg kg^{-1}). Soil pH_w is within the optimum ranges recommended for availability of nutrients and for groundnut production. Exchangeable K is no longer deficient. Sixty percent of the groundnut farms had a soil fertility score of less 0 and would need extractable P and exchangeable K replenishment.

At SFI_2 score 2 or greater the P, pH_w and K are optimum for maximum groundnut productivity. Management option for the groundnut farm will need to be maintaining the optimum levels. The prevalence of farms that with the SFI_2 score of 2 or greater was 34%.

The soil fertility scores provide useful soil fertility syndromes, which could be used to guide soil fertility management recommendations and field extension work. Table 3 shows the probability of a soil being above or below critical limits of pH_w, C, N, P and K,

Table 3 Probability of soil fertility constraints for different ranges of soil fertility index (SFI).

SFI_1		Soil fertility index range						
Soil nutrient	Selected range	$SFI_1 < -3$	$SFI_1 < -2$	$SFI_1 < -1$	$SFI_1 < 0$	$SFI_1 < 1$	$SFI_1 > 2$	$SFI_1 > 3$
TC	< 1%	100	95	86	83	73	0	0
TN	< 0.1%	100	96	89	85	75	0	0
Exch. Ca	< 4 $cmol_c\ kg^{-1}$	100	100	86	79	70	0	0
Exch. Mg	< 0.8 $cmol_c\ kg^{-1}$	100	95	78	58	48	0	0
SFI_2								
		$SFI_2 < -3$	$SFI_2 < -2$	$SFI_2 < -1$	$SFI_2 < 0$	$SFI_2 < 1$	$SFI_2 > 1$	$SFI_2 > 2$
Soil pH	pH < 5.3 units	-	83	54	41	29	0	0
	pH > 7.3 units	-	0	0	0	1	21	20
Extr. P	< 5 mg kg^{-1}	-	100	100	98	88	12	0
Exch. K	< 0.2 $cmol_c\ kg^{-1}$	-	83	53	44	33	8	0

Ca and Mg at different SFI_1 and SFI_2 soil fertility scores. These guides better represent the variability in the data compared with the average values given in Tables 1 and 2.

As SFI_1 falls below -1 there is an increasingly high probability, of greater than 73%, of C being below the critical deficiency limit of 1.0%. The same pattern applies to N, and exchangeable cations (Ca and Mg). For example, at $SFI_1 < -2$ there is 95% probability of being below the critical nutrient ranges selected. The probability of strongly acid soils (pH < 5.3) is 83% at $SFI_2 < 2$ and there is a high probability of P-deficiency (< 5 mg kg^{-1}) at $SFI_2 < 1$ rising to 100% at SFI_2 values of < -1. Exch. K has 83% probability of being low when SFI_2 drops below -1.

When the soil fertility scores for both SFI indicators is high there is low probability of prevalence in deficiencies of key nutrients in groundnut production systems. For example when SFI_1 is > 2, there is 0% probability of low C, low N, and Ca deficiency. At $SFI_2 > 1$ there is 0% probability of having strong soil acidity, but 20% probability of having high pH (> 7.3).

The soil fertility index framework provides a promising approach to linking soil IR spectral analysis to smallholder soil fertility recommendations [84]. MIR spectra of soil samples contain much information relevant to soil quality, and multivariate regressions of spectra from laboratory can accurately predict several soil nutrients prevalence. Many agricultural applications only require a classification of soil condition with respect to a critical test value for key properties to guide management decisions, similar to medical diagnostics. Shepherd & Walsh [22] were the first to propose the use of laboratory NIR analysis for the discrimination of soils falling above or below specific cut-off values for most properties related to soil fertility and further proposed the use of IR in diagnostic surveillance approaches (Shepherd and Walsh, 2007) [12]. They showed that soil samples could be roughly discriminated using classification trees even for properties like exchangeable K and extractable P, which are poorly predicted by regression models. This approach was further used by Cohen et al. (2005a) on an extensive data set of quality parameters for wetland soils, including soil microbiological attributes [85].

4. Conclusions

Strong relationships between soil reflectance and important soil nutrients (soil pH_w, C, N, Ca and Mg) and texture were found across diverse smallholder groundnut farms, spanning a range of soil types and AEZs in western Kenya, demonstrating the fundamental viability and potential of infrared spectroscopy as a rapid diagnostic tool for soil fertility assessment in small-scale production systems. Soil fertility indexes based on the principal components of soil properties provided a useful interpretative guide for soil fertility management interventions. Predictions of low extractable P and exchangeable K were possible when the soil properties were combined into a soil fertility index due to the inter-correlation among the soil properties. The soil fertility indicators were predicted well from the MIR spectra.

The soil fertility survey indicated that 56% of the groundnut farms had severe soil nutrient constraints for production and requires major soil fertility rehabilitation, especially with regard to exchangeable Ca, available P and organic matter. However, soil pH_w was within the recommended ranges in most cases for optimum groundnut productivity. Only 43% of farms had adequate soil fertility levels for groundnut production that would require only fertility maintenance.

This study demonstrates the utility of infrared spectroscopy as a diagnostic tool for rapid nutrient assessment in small-scale production systems. Further development and use of soil IR spectroscopy in large area soil fertility surveys is recommended towards evidence-based approaches for soil nutrient management. Further work is needed to directly relate crop responses to phosphorus and potassium to soil spectral properties.

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