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Full Length Research paper

Utilizing the infrared technology to characterize soil qualities in the Democratic Republic of the Congo's South Kivu province

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A fundamental prerequisite for effective land management is an understanding of soil properties. Conventional laboratory analysis has long been used to evaluate soil qualities, but it is expensive and time-consuming. As a result, alternative, quicker, and less expensive methods for soil analysis must be developed. Particular focus has been placed on chemometrics and infrared reflectance spectroscopy in recent years. Mid-infrared (MIR) and near-infrared reflectance (NIR) spectroscopy methods are quick, easy, and non-destructive ways to measure a variety of soil characteristics. The purpose of this study is to use infrared spectroscopy to characterize soil. For soil samples taken in the Democratic Republic of the Congo's Sud-Kivu province, this approach was used to forecast the soil's pH, soil organic C, total N, exchangeable Al, Ca, Mg, and K, CEC, and texture. Using a spatially-stratified random sampling design, 530 composite soil samples were collected from two sites (Burhale and Luhihi) at two depths (0–20 and 20–40 cm) over a 100 km2 area. It takes roughly two minutes to analyze a soil's MIR spectrum after minimal sample preparation. Disparities in soil depth and land use (cultivated versus non-agricultural) were assessed between the two sites. Standard wet chemistry techniques were used to evaluate a random subset of the samples (10%), and calibration models were created utilizing MIR data to estimate the soil parameters for the entire collection of soil samples. The partial least squares regression (PLS) approach produced solid predictions for all parameters with acceptable coefficients of determination ranging from 0.71 to 0.93. IR demands a large initial expenditure, despite being inexpensive for assessing soil parameters. Therefore, in order to make this technology usable in underdeveloped nations, technical and material help is required.

Key words: Spectroscopy, Prediction, Regression, Soil nutrient, Infrared.

INTRODUCTION

Education Soil One of the main causes of global food insecurity is the loss in soil fertility. Because farmers are unable to employ appropriate practices for yield development, the lack of precise information on soil management and sustainability at the farm level lowers soil productivity. The majority of research centers lack the necessary equipment to conduct research, and the majority of information pertaining to the nutrient content of the soil is unavailable. The majority of farmers cannot afford the extremely high laboratory fees associated with soil analysis. Due to the several steps required, the majority of research centers' existing wet chemistry procedures for soil analysis take a lengthy time to produce findings. Particularly in SSA, where soil fertility depletion is more severe, there is a pressing need for quick and sustainable methods of soil analysis to enhance fertilizer use and boost agricultural production. The efficiency of MIR in conducting quantitative analyses of soils, particularly soil carbon, has been shown in numerous investigations (Reeves et al., 1999; Shepherd and Walsh, 2002; Christy, 2009). Numerous qualities indicated by MIR spectra typically change only slowly in soils, meaning that once evaluated, re-analysis may not be necessary for that property or may only be necessary after a considerable period of time. Faster and less costly data collection methods are needed to quantify the many soil characteristics in order to conduct a thorough analysis of the roles played by a variety of soil physical, chemical, and biological characteristics in terrestrial ecosystems. This is particularly true for applications requiring exact spatial resolution of soil parameters, such as precision agriculture. Recent research has demonstrated that multivariate chemometrics and infrared reflectance spectroscopy can be used to quickly and affordably examine certain chemical and physical properties of the soil both qualitatively and quantitatively. As a result, infrared spectral investigations are perfect for inventorying soil resources (Minasny et al, 2008). Because of its quick, non-destructive, low-cost measurements and ability to identify multiple soil parameters at once, infrared reflection (IR) spectroscopy has drawn interest from soil scientists as a potential method for better soil analysis. The time has come to invest in soil health in order to boost productivity. Even extension services and research institutions that can help farmers in SSA understand the health of their soil do not provide them with knowledge on managing soil fertility. Infrared is a new technique for soil analysis that is quick and affordable, but it needs to be verified before being widely used. At the moment, there is little data to support its accuracy, which limits its application when it comes to land management decision-making. Therefore, the goal of this study is to evaluate the precision of this novel approach and utilize the findings to examine variations in soil samples taken from various locations.

MATERIALS AND METHODS

The study was carried out in the South Kivu province's eastern DRC. This area is described as by highland characteristics that receive a lot of rainfall and have a very high population density (Farrow et al., 2006). Figure 1 illustrates the two sites chosen for this investigation: Burhale and Luhihi.

Due to nutrient mining and erosion, overpopulation degrades South Kivu's soils. It also reduces the amount of land available for raising livestock, which lowers the number of animals that can provide manure for farmers (DSRP, 2005).

Agriculture is the primary industry in the area. Pigs, sheep, goats, chickens, and cattle are examples of traditional livestock. The Uvira plain is home to South Kivu's largest animal production area. However, because of overcrowding, there is less grazing space in Burhale (Walungu) and Luhihi (Kabare), which has resulted in fewer cattle. There are also large plantations of quinquina, tea, and coffee in the region (Mateso et al., 1998). South Kivu has a wide variety of soil types, most of which are influenced by their parent geology (Mateso, 1998). Based on the parent material, the soils of South-Kivu can be subdivided into four major groups:

1. Soils that have recently formed on volcanic substrate;
2. Soil developed on old volcanic substrate, mainly basaltic ;
3. Soils formed on old sedimentary and metamorphic rocks (cover extensive areas) and,
4. Alluvial soils and lacustrin and fluviatile deposits of the plains of Rusizi.

The 530 samples that were gathered were all scanned infraredly utilizing spectra of infrared reflectance between 400 and 7000 cm–1. Just a few grams of dirt (about 20 to 30 mg) were collected for the samples. Using an agate pestle and mortar, air-dried materials were ground to a fine powder (around N<100 µm). Aluminum micro titer plates contained 96 wells; an empty well was used to measure the background signal (Figure 2) (ICRAF, 2009,). The samples were loaded into the plates using a micro spatula to fill the 6-mm-diameter wells and level the soil, being careful not to spill into nearby wells. To adjust for variations in temperature and air humidity, background measurements of the first empty well were made prior to each individual measurement (Mevik and Wehrens, 2007). Since aluminum doesn't absorb infrared light, it can be used as a reference material (Terhoeven et al., 2010). To reduce specular reflectance, the bottoms of the Al wells were roughened. In order to account for within-sample variability as well as variations in particle size and packing density, soil samples were fed into four replicate wells, each of which was scanned 32 times (figure 2). The four spectra were then averaged.

According to the AFSIS technique, only 60 samples (about 10% of the 530 samples collected as advised by AFSIS) were subjected to wet chemical analysis (Vagen et al 2010). This indicates that the 60 samples underwent two analyses: wet chemistry and scanning.

The PLS (partial least squares regression) model, which combines the two data types for the prediction, was used to assess the prediction quality (Naes et al, 2002). The quality of the prediction was assessed using the root mean square deviation (RMSD) and coefficient of regression (R2) for the measured and estimated values (Tillmann, 2000; Brown et al., 2005). R software version 2.7.1 was used for the computations and statistical analysis (R Development Core Team, 2008). The strong R2 and low RMSD indicate that the calibration and prediction were successful; the estimated values are more in line with the actual values determined by direct wet chemistry. Good forecasts are regarded as having an R2 ≥ 0.75 for such a diversified data set (Shepherd and Walsh, 2002; Chang et al., 2001). Predictions with an R2 between 0.65 and 0.75 are deemed satisfactory, while those with a lower value are deemed bad (Shepherd and Walsh, 2002; Chang et al., 2001; Terhoeven et al, 2010).

RESULTS AND DISCUSSION

The **Soil parameters prediction Soil organic carbon**

Soil organic C was well predicted for the validation set (R^2= 0.72 and RMSE = 1.07; (Figure 4.1.). This shows that the prediction for this parameter was good. This finding agrees with other soil studies (Barthe et *al*. 2008; Ludwig et *al*. 2008). The results also agree with those of Rossel et *al*. (2006) who reported similar accuracy (R^2 = 0.73) for a much less diverse validation set of 118 samples from 18 ha agricultural field in Australia.

Similarly, from a global study, Terhoeven *et al.* (2010) reported *an* R^2= of 0.8 Soil organic carbon (SOC) is a key attribute of soil quality, which influences a variety of biological, chemical and physical properties of soils (Carter, 2002). Consequently, methods to accurately determine SOC are necessary to achieve a better understanding of the nature and dynamics of SOC (Denm8ef *et al*., 2009). Soil organic carbon is an indication of soil organic matter content, which acts as both a source and sinks for nutrients. Soil organic carbon is linked to soil chemical, physical and biological health, and is strongly correlated with soil nitrogen supply in term of soil fertility management. The satisfactory prediction of SOC (R^2<0.75) helps to monitor the soil status from the study area for a sustainable soil management. A study in Canada reported good prediction (R^2=0.92) (Madari et *al.,* 2006) than the current study. However, according to Shepherd and Walsh (2002) and Chang *et al*. (2001) predictions of R^2 ranging from 0.65 to 0.75) are satisfactory.

Extractable Aluminum

Extractable Extractable Aluminum was also well predicted t (R^2= 0.71 and RMSE = 1.07 (Figure 4.2).

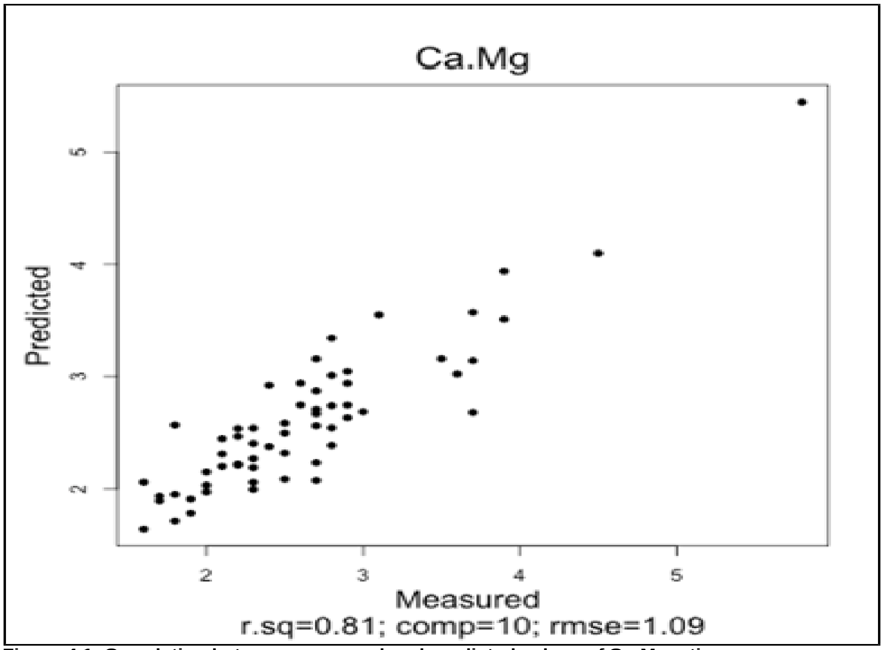

Figure 4.1: Correlation between measured and predicted values of Ca:Mg ratio

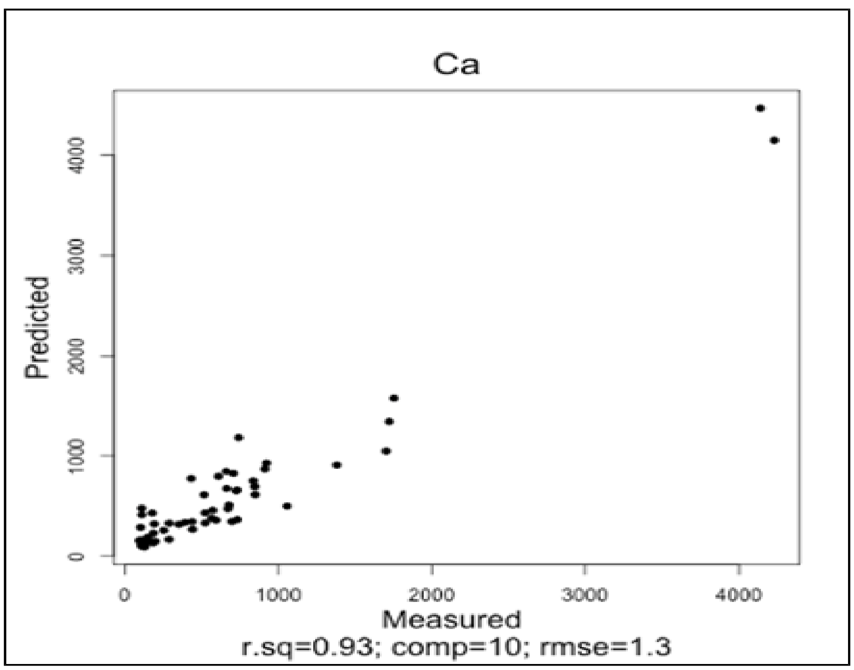

Figure 4.2: Correlation between measured and predicted values of Ca:Mg ratio

Based on the given prediction criteria, this indicates a good forecast of this parameter (Terhoeven et al., 2010). An R2 of 0.71 was obtained by several investigations (Brusetal, 2002; Borggaard et al., 2004). But according to Madari et al. (2006), who used Canadian soils, their results showed a superior prediction (R2=88) than the current study that may otherwise be lost from the soil rooting depth. Better phosphorus control will be encouraged by less expensive methods of measuring iron and aluminum oxide concentration. lessen the pollution caused by nutrients. The MIR's prediction of this parameter opens up a new area for soil fertility monitoring in the DRC's eastern highlands.

Calcium: Magnesium ratio

The coefficient of correlation between actual measurements and predictions by PLS model for Ca: Mg

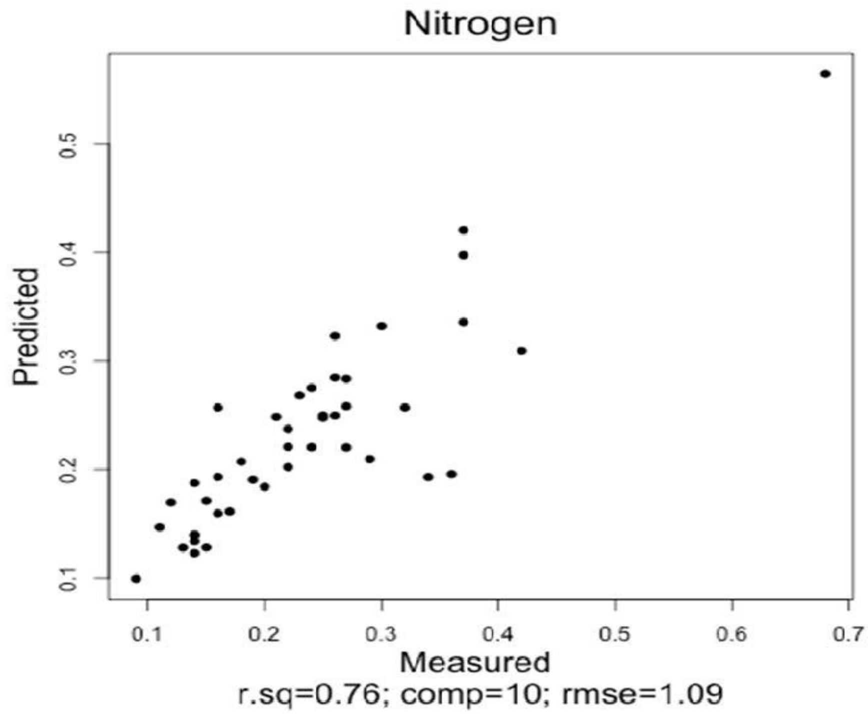

Figure4.3: Correlation between measured and predicted values of Total N

ratio using the independent validation set of 60 samples was R2 of 0.81 (Figure 4.3).

Compared to the results obtained in Australia (Minasny et al., 2009), which showed that MIR cannot accurately predict the Ca:Mg from that region, the current study provided a better prediction (R2=0.81). However, Dunn et al. (2002) found that the 178 samples they collected from Canada showed the currency of Ca/Mg ratio prediction (R2=0.81), which is consistent with the current findings.

Exactable Calcium

The R2 values and RMSE indicated that the extractable calcium prediction was good (Figure 4.4). The model for the soil Ca analysis was validated since the coefficient of regression was high (R2 = 0.93), indicating a solid prediction of the parameter. This indicates that based on the successful model prediction, Ca, which was predicted in the current study, may be employed appropriately for evaluating soil aptitude.
The study's validation predictions for Ca are superior to those of other authors' findings. For instance, McCarty and Reeves (2006) reported an R2 of 0.77 for extractable calcium in a study conducted in the USA, which is still less than the current study. Similarly, R2 = 0.84 was obtained for prediction values by Viscarra et al. (2006) and McCarty and Reeves (2006). Additionally, the model created in this study produced superior results than others published worldwide, such as Terhoeven et al. (2010), which reported R2 = 0.61 with an RMSE of 1.64. The current study's accurate Ca prediction helps with soil nutrient evaluation and enables the recommendation of using an IR scanning approach for this element.

Total Nitrogen (TN)

In terms of the R2 and the RMSE, Total Nitrogen provided a decent prediction (Figure 4.5). There is a good correlation between the direct and anticipated values, as indicated by the regression coefficient of 0.76. This accurate TN prediction opens up a new way to quickly evaluate this soil element. The most crucial soil nutrient for agricultural development in SSA can now be analyzed, which opens up new avenues for soil nutrient assessment.

These findings are consistent with those of other writers. For instance, Minasny et al. (2009) found that the same ratio (R2=0.76) was found in a study that was done on Australian soils. The similar value of R2=0.76 was reported by Reeves et al. (2006), Cozzolino and Moro (2006), Barthe et al. (2008), and Vasques et al. (2009) in research conducted in areas with significant agroecological variability. However, given the prediction is good (R2>0.75) by the criteria, the accuracy is still good. This indicates that the prediction's accuracy is also influenced by the region's soil variability. Consequently, the fact that the soil samples utilized in the Canadian investigation came from the same region and belonged to the same soil type may have contributed to the high calibration performance that was noted (Reeves, 2006).

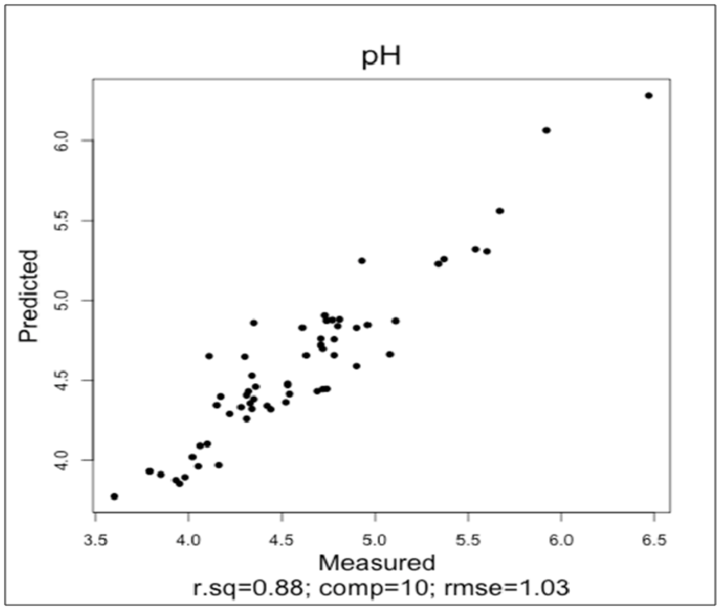

Figure 4.4: Correlation between measured and predicted values of pH

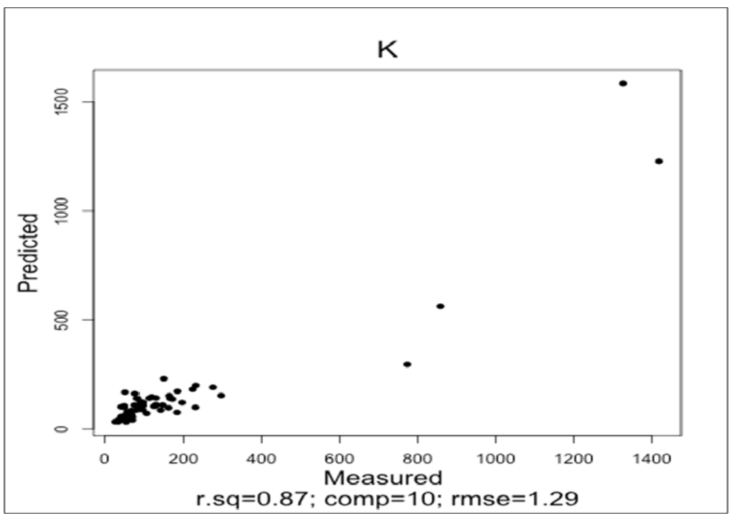

Figure 4.7: Correlation between measured and predicted values of extractable K

Soil pH

With R2 = 0.80 and RMSE = 2.21, the pH of the soil was accurately predicted (Figure 4.6). These results are consistent with those of McCarty and Reeves (2006), who used MIR analysis to analyze 544 soil samples from 272 locations in a single field in the United States (R2 = 0.8). Similarly, Terhoeven et al. (2010) found that their research of the Australian landscape yielded an RMSE of 0.75 and an R2 of 0.8 worldwide. The biggest issue with land degradation in the DRC is soil acidity, which is currently reducing agricultural output. The management of soil acidity will be substantially aided by methods that support the measurement of soil pH, the calculation of the rate of lime needed to reach an acceptable pH, and the quality of lime products.

Janik and Skjemstad (1995) reported an R2 of value 0.72 (acceptable prediction) for 291 Australian soils, which is marginally better than the results of the current study. According to Reeves (2009), additional elements including organic acids and carbonates affect infrared's capacity to forecast pH. These results of satisfactory prediction suggest that MIR spectroscopy may be able to forecast this parameter.

Extractable Potassium

Extractable potassium was well predicted with the regression model having R2=0.87 (Figure 4.7).

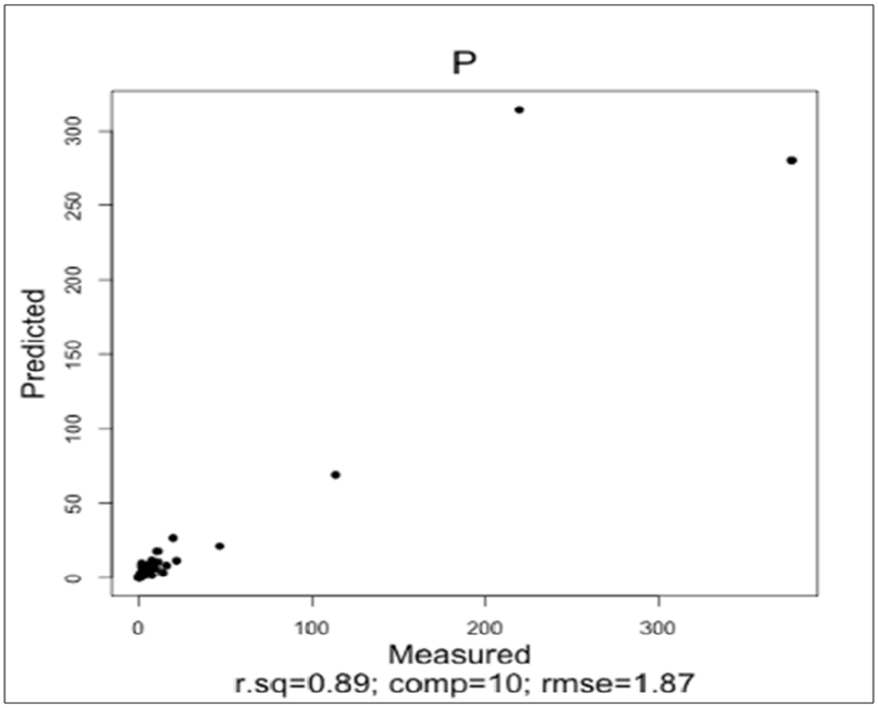

Figure 4.8: Correlation between measured and predicted values of extractable P

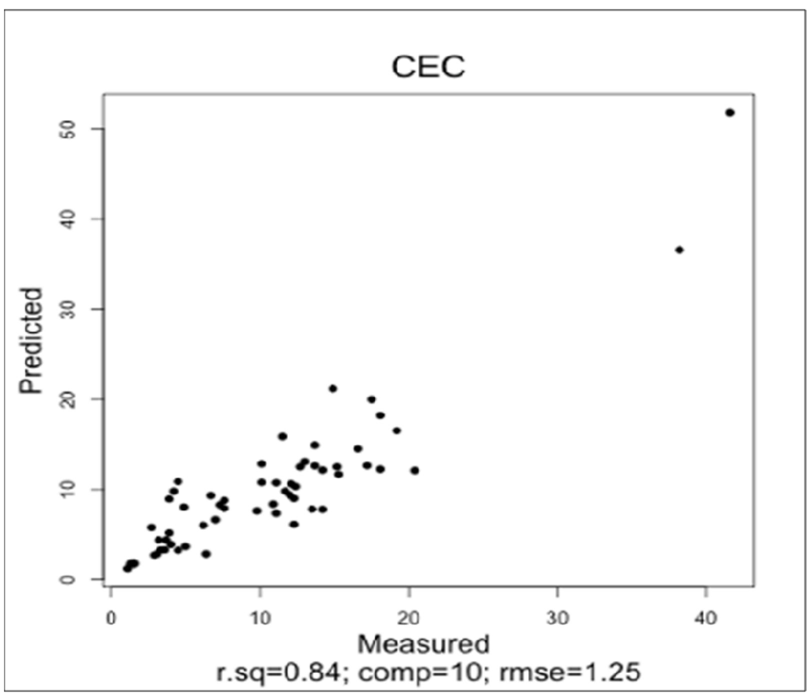

Figure 4.9: Correlation between measured and predicted values of CEC

These findings demonstrate how well potassium may be predicted spatially within the research area. The model is helpful for this parameter because of its accurate prediction of K (Shepherd and Walsh, 2002; Chang et al., 2001).
This is in line with the findings of Hartemink (2006) and Lark (2009), who discovered that 178 samples from the Australian landscape had good K predictions. The possibility of evaluating the soil condition in the study area using the estimated values for K is made possible by the prediction's accuracy.

Extractable Phosphorus

In this investigation, extractable P was accurately predicted with R2=0.89 (Figure 4.8). This suggests that the model's P determination is validated. These findings are in good agreement with those of a study done on Australian soils by Minasny et al. (2009). They also concur with those of Sellitto et al. (2009) from India, who reported an R2 of 0.90, and Hartemink (2006) and Madari et al. (2006), who reported values of R2 = 0.85 and 0.93, respectively, from the Canadian landscape.
Although Hartemink (2006) showed a satisfactory prediction of this parameter with an R2 of 0.57, several Canadian studies have reported poor predictions, such as those made by Madari et al. (2006) from the Canadian landscape and Sellitto et al. (2009) from India. This excellent modeling of P in the eastern Democratic Republic of the Congo creates a new avenue for evaluating this crucial crop production nutrient.

Cation Exchangeable Capacity

This method's validation for CEC yielded an R2 value of 0.84, suggesting that CEC was accurately predicted (Figure 4.8). Several research (Dunn et al., 2002; Sellitto et al., 2009; Richter et al., 2009) have shown that MIR offers accurate forecasts for CEC in various locations, such as India, Canada, and the US, respectively. Similar prediction accuracy for this measure was demonstrated by Pirie et al. (2005) for 415 samples from southeast Australia.
In the current study area, the R2 value for CEC is 0.84 (Figure.4.9), indicating that the direct and estimated values for this parameter are closer to the expected values. Similar to Pirie et al. (2005) from soils in south Australia, Sellitto et al. (2009) from India likewise obtained strong predictions for this parameter. The soil science research can bypass many of the limitations of traditional laboratory analysis because to this excellent modeling of CEC.

Soil physical particles prediction

Particle size effects on light transmission and reflection, and strong absorption features exhibited by water, explain the accurate predictions for texture (Cécillon et al, 2009; Chang et al., 2001).
Predictions for particle size were satisfactory for clay (R2 = 0.74 and RMES = 1.05); sand (R2;= 0.81 and RMES = 1.08) and silt (R2 = 0.84 and RMES = 1.06).
These results are broadly similar to those of previous researchers (McCarty and Reeves, 2006; Pirie et al., 2005). Terhoeven et al, 2010 got similar results globally (clay (R2 = 0.73 and RMES = 1.85).
All these tree physical parameters respond to the calibration requirement (Chang et al., 2001; Shepherd and Walsh, 2002; Terhoeven et al, 2010) and validation of the results is correct.

CONCLUSION

This study sought to determine whether a new method of soil characterization based on the Infrared Scanning (IR) technology might provide quick and accurate soil property quantification. Overall, the results demonstrated a good and satisfactory prediction model with above 75% for both the physical features of the soil and all of the chemical parameters under investigation (pH, Al, P, N, Ca, K, PSI, Exchangeable acidity, and CEC). Phosphorus had the best prediction of any of the factors studied (R2=0.93), while all other parameters had R2 values greater than 0.75, with the exception of SOM and TN, which had R2 values of 0.73 and 0.71, respectively. It is suggested that the IR scanning method be used to determine the qualities of soil because it predicts all chemical parameters well. The approach is also quick and cost-effective. It took two days to scan the 530 samples, when using traditional soil analysis techniques could have lasted over two months. With R2 values of 0.81, 0.84, and 0.74 for sand, silt, and clay, respectively, the prediction of soil particles was likewise good for all three parameters. This suggests that the infrared scanning method is a trustworthy way to determine the texture of soil. This method is still relatively new, though, and few scientists have been able to apply it. Even at a low level, this approach cannot be employed without the combination of wet chemistry results. To monitor soil and land degradation in underdeveloped nations, further work is required to enhance the application of infrared scanning. IR demands a large initial expenditure, despite being inexpensive for assessing soil parameters. Therefore, in order to make this technology usable in underdeveloped nations, technical and material help is required.

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