mapping soil nitrogen from geospatial Interpolation and remote sensing.

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ABSTRACT

Nutrient mapping is common in most agricultural countries. However, the prediction of nitrogen using remote sensing in areas where it is needed the most has been proven to be scarce. The main objectives of this study were to 1) test the accuracy of soil nitrogen maps produced from geostatistical interpolation; and 2) to test whether there is a relationship between soil nitrogen and the normalised difference vegetation index. Soil samples were collected in 100m² randomly selected for later laboratory tests using the Kjeldahl method. The results from soil sampling showed that nitrogen content in the Black soils was 0.103 whilst it was 0.064 in the red soils. T-test results showed no significant differences between Nitrogen% content in the Red and Black soils (p = 0.4). Landsat-based NDVI ranged from 0.1 to 0.5, suggesting that vegetation cover was intermediate in the study area. The results of regression analysis seemed to indicate existence of a strong negative relationship between NDVI and N content both in the Red and Black soils. The results of this study provide useful insights on how infield variation in soil nitrogen can be mapped and how the output from the mapping could be used in selective application of fertilizer in agricultural landscapes.

Keywords: Mapping, remote sensing, geostastistical, soils, nitrogen, prediction.

INTRODUCTION

The mapping of soil physical properties from Geostatistical interpolation and remote sensing is a well described phenomenon in scientific literature (Burgess and Webster, 1980; Sanchez et al., 2009; King et al., 1994). As such, several soil physical properties have been described at both the global (e.g., Sanchez et al., 2009; FAO., 1989) and regional scales (d’Hoore and D’Hoore, 1964; King et al., 1994). These soil-based products have been used extensively in ecological (Ettema and Wardle, 2002; Davidson and Lefebvre, 1993), as well as agricultural studies (Anderson-Cook et al., 2002). In more recent years, the demand for soil physical properties maps increased due to advancements in precision agriculture (Adamchuk et al., 2004; Córdoba et al., 2016; Khanal et al., 2017) which requires precise information on soil nutrient availability at particular locations for the precise application of inputs. This is so because most agricultural soils suffer from nutrient deficient, particularly nitrogen, which is one of the key limiting factors in the tropical agro ecosystems which has resulted in low yields (Wood et al., 2015). Crop yield is always poor when nitrogen is deficient (Havlin et al., 2005), this implies that high nitrogen content in soils is associated with high soil quality. Crop yield has been shown to decrease by an average of 25% under nitrogen limited environments (Ding et al., 2018), this means that there is a robust relationship between nitrogen and yields (Bodirsky et al., 2014). Regarding nitrogen levels, studies observed that there is 30-40% nitrogen deficient on cultivated soils (Pardo et al., 2007). Thus Nitrogen supplements of ~150kgs per hectare are required to maintain soil N stocks for an average yield (Ding et al., 2018; Havlin et al., 2005). Maps are available of different resolutions which are used to predict nitrogen as well as those that show physical properties of soil which farmers use in their day today farming activities.

Although maps of soil physical properties are available,
even at a free cost, they are usually at coarse spatial resolutions (Hengl et al., 2014; Batjes, 2016), thus rendering them less useful when fine scale work such as precision agriculture has to be implemented. For instance, soil properties data at 250m could be useful for large scale ecological studies but may be less useful for precision agriculture. This is largely because there could be major spatial variability in soil nutrient properties within the 250 by 250 m grid. It is also generally agreed that soil physical property maps produced from Geostatistical interpolation are more accurate in landscapes where sampling was intensive (Reza et al., 2015). Accuracy is generally lost in areas where sampling is less intensive. Most global products could therefore be less accurate at sites where sampling was not intensive.

Thus studies that seek to enhance the accuracy of soil properties mapping provide important information in projects such as precision agriculture. The current study sought to: 1) to test the accuracy of soil nitrogen maps produced from geostatistical interpolation; and 2) to test whether there is a relationship between soil nitrogen and the normalised difference vegetation index.

**MATERIALS AND METHODS**

The study was carried out in a grid pattern of two 100m by 100m plots in an agricultural field at the University of Zimbabwe farm (Thorn Park Estate) located 8km away from the University Mount Pleasant Campus along the Harare- Mazoe Road (Figure 1). The farm is 1636 ha in extent. There are fersialitic soils and para-fersialitic soils in the area (Red and Black soils), (Vincent and Thomas, 1960).

To test for the optimal sampling interval, we first calculated the spatial autocorrelation of the Landsat 8 maps of the study area for each band (band one to 12). Then, we calculated the mean range of the combined variograms to come up with one variogram which shows the spatial range or extent of the spatial autocorrelation. The result suggested that the range was 250m on average. This implied that there was spatial autocorrelation up to 250m and beyond which was no autocorrelation. This was used to determine our sampling interval, that is, below 250m. In the field, a 100 by 100m grid was established and the points were assigned along each transect 8points to the north and 9 points to the east.

We managed to sample 105 points from two different fields: one from the black soils and the other from the red soils. We sampled 56 plots from red soils and 49 from black soils at an interval of 16 m, taking amount of soil of 500 g per point out of a 25cm by 25cm hole. A Global Positioning System (GPS) was used in the field to navigate to points of soil sample collection. A tape measure was also used to measure distance for correct points of collection and then the soils were taken to the laboratory for analysis.

In the laboratory, the soils were dried and analysed for nitrogen content using the Kjeldahl digestion procedure (Kjeldahl, 1883). Materials that were used comprised a Kjeldahl assembly (Digestion and distillation and titration), burette, conical flask, Measuring cylinder, volumetric flasks and soil samples.

Firstly, 5 g of dried soil were weighed accurately and placed into a Kjeldahl flask. This was repeated for all 105 samples. Secondly, 2 g of powdered potassium sulfate, 0.5 g of cupric sulfate, and 20 ml of sulfuric acid to the samples were added to the measured soil. Then the flask was placed on to the Kjeldahl digester and the contents were digested until the contents became a clear, blue solution. The contents were heated for 1 h, cooled and 150ml of water was added gradually before cooling. Then 25 ml of 0.05 mol/l sulfuric acid was measured and transferred into a conical flask. We added 80ml of water to the receiving flask on the distiller, and immerse the lower end of condenser of the Kjeldahl distillation into the solution. Two granules of boiling tips or granulated zinc were then added into the Kjeldahl flask from digestion, and gradually add 85 ml of concentrated sodium hydroxide solution. Immediately, we connected the flask to the distillation apparatus and applied heat gently. As soon as the contents reached boiling point, we turned up the heat, and distil until about two thirds of the contents were distilled. The lower end of the condenser was removed from solution, and continued with the distillation for a short time, then we washed the lower end with a small quantity of water, and removed the conical flask from the assembly.

Thereafter, 5ml of methyl red indicator was added into the flask with the distilled contents and titrated the excess acid in the conical flask with 0.1 mol/l sodium hydroxide solution using Methyl red indicator to confirm the end point. The endpoint is the volume of solution when the color of solution changes from red to yellow. A blank test was performed to make any necessary corrections.

To calculate the amount of nitrogen in the soil sample measured, we divided the amount of nitrogen by the soil mass and convert it to a percentage. Firstly we run the statistical analysis of the recorded nitrogen in a GIS (using SPSS), as shown in Table 1.

The recorded data were analyzed in a GIS using (Illwis), to interpolate the spatial variation of nitrogen in the soil using moving average and moving surface. The prediction accuracy of the two interpolation method was evaluated using one validation sample set containing 10% of the total data (n=6 for the black soils, n=5 on the red soils). Estimation techniques were evaluated using root mean square error of prediction between measured and predicted values of samples in the validation dataset as an indicator of estimation error. Lower RMSE indicates better methods. RMSE is formulated as:

\[ \text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2} \]

Where x predicted and y observed are the variables of
Table 1: Descriptive statistics of measured variables.

<table>
<thead>
<tr>
<th></th>
<th>Black soil</th>
<th>Red soil</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.1028</td>
<td>0.0640</td>
</tr>
<tr>
<td>Std. Error of Mean</td>
<td>0.00691</td>
<td>0.000837</td>
</tr>
<tr>
<td>Median</td>
<td>0.1196</td>
<td>0.0296</td>
</tr>
<tr>
<td>Mode</td>
<td>0.11</td>
<td>0.01</td>
</tr>
<tr>
<td>Std. Deviation</td>
<td>0.04836</td>
<td>0.06206</td>
</tr>
<tr>
<td>Variance</td>
<td>0.002</td>
<td>0.004</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.957</td>
<td>0.950</td>
</tr>
<tr>
<td>Std. Error of skewness</td>
<td>0.340</td>
<td>0.322</td>
</tr>
<tr>
<td>Range</td>
<td>0.15</td>
<td>0.22</td>
</tr>
<tr>
<td>Minimum</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td>Maximum</td>
<td>0.16</td>
<td>0.23</td>
</tr>
</tbody>
</table>

Figure 1: Study area showing University of Zimbabwe farm.

Interest predicted using geo-statistical methods and measured in the laboratory, respectively. Moreover, we downloaded the Landsat 8 image of the study area for the month of November, and we calculated NDVI for the study area from land sat 8 image bands using the formulae:

\[
NDVI = \frac{NIR - R}{NIR + R}
\]

(Rouse et al., 1973)

Where NIR is Reflectance in the Near Infra-red; R is the Reflectance in the Red Band.

Moreover, we then made an analysis of the relationship between Nitrogen measured and remote sensing data in S-plus using linear regression (Figure 3).

To test for the optimal sampling interval, we first calculated the spatial autocorrelation of the Landsat 8 maps of the study area for each band (band one to 12). Then the mean range of the combined variograms was calculated to come up with one variogram which shows the spatial range or extent of the spatial autocorrelation. The result suggested that the range was 250m on average. This implied that there was spatial autocorrelation of up to 250m and beyond which was no autocorrelation. We used this to determine our sampling interval, that is, below 250m. In the field, a 100 by 100m grid was established and
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RESULTS

The amount of nitrogen was found to be the same in both the red and black soils (t = , p=0.4225). The mean percentage of nitrogen was observed to be 0.1028 in the black soils and 0.0640 in the red soils (Table 1). The highest amounts of nitrogen were observed in the red soils (N = 0.24).

Figure 2a shows the spatial variation of N in the site with black soils. It can be observed that N varies spatially across the field. Specifically, lower N% is observed in the northern north-western and eastern parts of the field. However, the rest of the field has relatively higher N levels. Figure 2b shows the in-field N% spatial variation in the red soils. It can be observed that the centre parts of the field show low N%, while the northwest, southwest and southeast of the field show relatively higher N%.

Figure 3 shows significant (P < 0.05) negative relationships between N% and NDVI in the red and black soils, respectively. Absolutely, it was observed that NDVI explains 90% of the variance in N% in red soils, while it explains 83% of the variance in N% in black soils.

The root mean square error was calculated and determined as 0.025

DISCUSSION

The interpolation technique moving surface was applied to the N% data sets to produce detailed maps of N% variation in the red and black soils. The moving surface interpolation technique produced the least error when tested for accuracy using an independent data set. This result is supported by the findings of Mulla et al. (1992) where moving surface interpolation results were found to be better than simpler methods such as inverse weighting or trend surface models. We found out that interpolated nitrogen in both the red and black soil fields accurately represented spatial variability in nitrogen levels in the

Figure 2: In-field spatial variation in N% in the field sites based on the moving average, a) illustrates the spatial variation of N% in the site with Black soils, and b) illustrates the in-field N% spatial variation in the Red soils.
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study area. In fact, cross validation with 10% of the sampled points produced a small root mean square error of 0.025 which is between the range of values of the predicted and the observed values of nitrogen percentage. This means that predicted values are close to observed values, hence the model used is significant. The level of nitrogen in soil samples was also found to be negatively related to NDVI in both the red and black soils (p<0.05). The reported accuracy of interpolation results could mean that in large landscapes where sampling is not possible for every grid cell, interpolation may be considered as a way to map spatial variability in nitrogen levels across agricultural landscapes. In addition, the significant relationship between nitrogen levels and NDVI could imply that remotely sensed data can be used to predict and map spatial variation in nitrogen levels. The application of both interpolation and remote sensing in mapping nitrogen could open newer opportunities in efforts aimed at precise application of fertilisers for enhanced agricultural production.

The finding that spatial interpolation can accurately map spatial variability in geographic phenomena is not surprising since this has been reported extensively in earlier studies (Jeffrey et al., 2001; Li and Heap, 2011; Lam, 1983). In addition, the observed relationship between soil nitrogen and NDVI is in line with earlier studies that reported an exponential relationship between NDVI and N uptake (Lukina et al., 2001; Liu et al., 2005; Stone et al., 1996). Moreover, Craine et al. (2003) also found a significant negative relationship between soil N and the biomass of plants. Therefore, we can deduce the relationship between NDVI and N in the soil can be used for farm crop management for precision agriculture.

While the utility of spatial interpolation techniques is not questioned in literature, its accuracy in mapping spatial variation of nitrogen, especially in African savannah landscapes remains largely unconfirmed. Our results therefore provide a foundation for further hypotheses that test for the accuracy of interpolation for precision agriculture. The accuracy of interpolation results in our study could be as a result of the high spatial autocorrelation in nitrogen measurements in both the fields characterised by red and black soils. Absolutely, initial analysis revealed that there is spatial autocorrelation in nitrogen to a distance of 250m (mean range = 250m). Thus the results suggest that in landscapes characterised by high spatial autocorrelation, interpolation can be used with confidence since it yields high Accuracy.

The major strength of this study lies in the fact that data analysis was robust. For instance investigation of spatial structure was first performed using the semi-variogram and later validation of interpolation results conducted using the root mean square error. However, due to resource limitations, soil samples were collected and analysed in a small area. Future studies could therefore replicate the analysis in larger landscapes in order to establish whether the accuracy of results is not confounded by the size of the study area. In addition, interpolation can also be attempted in non-agricultural landscapes in order to test whether the accuracy of interpolation is accurate in landscapes characterised by different land use. While NDVI is a good index in vegetated landscapes, its applicability is limited when the ground is bare. Thus future work could test for utility of remote sensing in mapping nitrogen in areas with bare soils.
Mapping of the spatial variability in soil nutrients such as nitrogen from both interpolation and remote sensing opens opportunities for rapid mapping of such variability in large landscapes. The resultant maps are useful in many fields of specialisation which also include precision farming.

Where this study differs from previous studies is in its focus on the southern hemisphere tropical savannah soils. Previous studies on precision agriculture have mainly been based on the northern hemisphere mainly at a large scale. In addition, traditional crop management in Zimbabwe has mainly considered any field area homogeneous in terms of rainfall amounts, altitude, and productivity potential (Vincent and Thomas 1960; Anderson et al. 2004). Furthermore, the use of GIS science for precision agriculture is also very important in that it lessons labour and allows accurate measurements of variability within the fields. Nitrogen is a key limiting factor in tropical agro-ecosystems resulting in low yields. People have resorted to blanket fertilizer application which is not economic in nature. So, lack of knowledge on how nutrients especially nitrogen vary in space is a main problem that have affected the tropical agro-ecosystems.

The strength of this study is that it focuses on the in-field nitrogen variation in maize fields, which is a very important aspect to farmers in the southern part of Africa since it will allow them to move from the traditional way of applying fertilizer. Farmers will move towards the scientific way of applying fertiliser and it benefit them economically. Instead of applying the equal quantities of nitrogen fertilizer uniformly in a field, this study helps much in informing how fertilisers can be applied in relationship to specific requirement of a point, thereby saving costs. However, the research lacks information on other nutrients such as potassium, phosphorous among others. This is a demerit in that these are also some of the nutrients that a plant cannot survive in their absence.

Future research should look into the thematic issue in a much more advanced way. There is need for predicting the in-field nutrient variation in crop fields as well as the estimation of yield using some other geotechnological.

Conclusion

In this study, it was found that soil nitrogen in agricultural landscapes can be accurately mapped from spatial interpolation, as well as remotely sensed indices such as NDVI. These findings provide a platform for formulating hypotheses that seek to accurately map spatial variability in soil nutrients even in large landscapes. Such maps are invaluable in several fields of specialisations which include precision agriculture aimed at enhancing food security without wasting inputs.

REFERENCES


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