Low intensity sampling based predictive model for actual soil volume

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ABSTRACT

Soil-landscape modeling is one of the important researchable issues in soil science. Literature is scanty on such models especially using low intensity sampling and such models are unknown in rubber (Hevea brasiliensis) growing areas in Kerala. Prior visualisation of study area using a digital elevation model (DEM) with 90 m resolution was found useful in selecting the sites for soil profile excavation. Eleven soil profiles were cut and characterized and the resultant regression model i.e. actual soil volume (ASV) = -0.091 + 23.9 depth – 0.99 coarse fragments – 0.98 porespace (adjusted R² = 0.999) indicated a very good relation. Predictive maps were generated with data on 9 soil profiles using inverse distance weighting (IDW) method. The predictability, as tested by two samples i.e. soil profile 3 and 9 (which were excluded from model development), was 94, 89 and 82%, respectively for depth, coarse fragments and slope. Similarly, the error in prediction of ASV was 18 and 19% for soil profile 3 and 9, respectively. Nevertheless, the actual and predicted values placed the soils in the same class of slope and depth thus making the error in prediction ignorable. However, there are no such ranges identified to describe ASV and the coarse fragments with weighted means. The results of low intensity soil sampling (one soil profile per 4.4 ha) and interpolation with IDW are encouraging and this technique can help in generating predictive maps of similar such terrains at a lesser cost with acceptable error.

Key words: Actual soil volume, Inverse distance weighting, Low intensity sampling, Soil-landscape modeling

Accurate mapping of soil properties is a critical constituent of successful site-specific agriculture (Rossel and McBratney, 1998), which is an integral part of precision farming. A substantial amount of research has been conducted regarding the appropriate number of samples needed to characterize a central tendency of a soil property with a specified degree of accuracy (McBratney and Webster, 1983; Webster and Oliver, 1992). It was documented that larger the number of samples, more accurate the map of soil property (Mueller et al., 2001). However, the cost of sample collection and analysis can quickly exceed any potential benefits from applying site-specific management (Kravchenko, 2003). Obviously, some focus is necessary on low intensity sampling to develop prediction model even for small farms. There are various perceived benefits of predicting the soil variability using landscape-modeling approach. An important advantage is that it can reduce the need for extensive field sampling and costly laboratory analysis by minimizing the number of samples needed to generate spatial predictions (Chaplot et al., 2001).

Basically, the terrain that supports rubber plantations traditionally in Kerala and Tamil Nadu is highly undulated in midlands (30-300 m above msl) and lower portions of highlands (>300 m above msl) (NBSS and LUP, 1999). In this kind of undulated topography, which results in soil variability, it is necessary to understand landscape-soil relationships to help precision farming. Hence, a study was taken up with objectives (i) to visualise the study area using freely available digital elevation models to select the sites for soil profile studies; (ii) to characterize soil profiles occurring on different slope positions; and (iii) to test the prediction power of maps generated by interpolation of soil profile data after low intensity sampling.

MATERIALS AND METHODS

Visualisation of the terrain

Digital elevation model of the study area, acquired during Shuttle Radar Topography Mission was freely downloaded (http://www2.jpl.nasa.gov/srtm/) and visualized in three dimensions using freely available software 3DEM (version 20.4, http://www.softpedia.com ).

Soil sampling and analysis

Eleven soil profiles were excavated to hard rock or up to 150 cm on top, mid and bottom slope positions on different hills after visualisation of the study area. Handheld Garmin V GPS receiver was used to ascertain latitude and longitudes of soil profile locations. Point vectors of soil profiles were superimposed on DEM and landscape attributes like slope, elevation and aspect at the profile sites were extracted using Hawth tools integrated to ArcGIS (version 9).
Samples were drawn from all horizons with core sampler of known volume (440 cc, with 10.8 cm length and 7.2 cm inner diameter). Bulk density (BD) and particle density (PD) of soil samples were determined by standard procedures (Blake and Hartge, 1986a; 1986b). The dried soil clods were crushed and coarse fragments (>2 mm size) were separated using 2 mm sieve. Volume of coarse fragments was determined by a simple water displacement method as was suggested by Rao and Vijayakumar (2005). Using BD and PD, the pore space in each core was calculated. Actual soil volume (ASV) in the core was derived by volume of pore space and coarse fragments from that of core. The weighted mean of ASV per tree was calculated using the spacing (4.9 m x 4.9 m) and horizon thickness as the inputs. Textural analysis of fine earth was also done for all horizons.

**Data processing**

Regression of actual soil volume on volume of coarse fragments, pore space and depth was tested to understand the relationship using SPSS (Statistical Package for Social Sciences) version 13.0 (SPSS Inc., 2004).

**Map generation**

Out of 11 data points, nine were used for interpolation by inverse distance weighting (IDW) technique (Ries, 1993; Kravchenko, 2003) and maps of slope, depth, coarse fragments and ASV were generated using ArcGIS (version 9). These interpolated models were tested for their power of predictability using data on profile 3 and 9, which were not included in model development and selection of these two points was purely random.

**RESULTS AND DISCUSSION**

**Study area (Terrain)**

Three dimensional visualisation of study area as viewed from four directions helped to understand the relief in different directions (Fig. 1). The location of soil profiles was also shown in the figure as numbered dots.

**Landscape attributes at soil profile locations**

Certain landscape attributes like elevation and slope were extracted from the DEM pertaining to soil profile locations and given in Table 1. The elevation ranged from 74 m to 140 m while slope varied between 6 to 25%.

**Soil characteristics**

Soil profiles varied in depth from 0.6 m to 1.6 m indicating the degree of variability (Table 1). The assumed volume of solid space per tree exhibited high variability, which ranged from 9.1 (profile 4) to 30.6 m$^3$ (profile 1) and this extent of variability is not ignorable. Similarly, the content of coarse fragments also varied (30 to 42% of solid space) and quantitatively ranged from 2.9 (profile 4) to 9.7 (profile 1) m$^3$ per tree. Pore space also exhibited variability from 3.5 (Profile 6) to 14.0 m$^3$ (profile 7). Obviously, resultant ASV varied accordingly (58 to 70% of solid space) and it quantitatively ranged from 6.2 (profile 4) to 20.9 m$^3$ (profile 1). Among the soil particles, sand...
Table 1. Landscape attributes and properties of soil profiles

<table>
<thead>
<tr>
<th>No.</th>
<th>Altitude</th>
<th>Slope</th>
<th>Depth</th>
<th>Volume of solid phase per tree</th>
<th>Pore space</th>
<th>CF</th>
<th>ASV</th>
<th>sand</th>
<th>silt</th>
<th>clay</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>m</td>
<td>%</td>
<td>m</td>
<td>% of solid phase and content (m$^3$) (in brackets)</td>
<td>tons m$^{-3}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>95</td>
<td>10</td>
<td>1.63</td>
<td>30.6</td>
<td>8.5</td>
<td>32 (9.7)</td>
<td>68 (20.9)</td>
<td>1.18</td>
<td>0.13</td>
<td>0.52</td>
</tr>
<tr>
<td>2</td>
<td>74</td>
<td>8</td>
<td>1.34</td>
<td>21.5</td>
<td>10.7</td>
<td>42 (9.1)</td>
<td>58 (12.4)</td>
<td>1.18</td>
<td>0.25</td>
<td>0.75</td>
</tr>
<tr>
<td>3</td>
<td>87</td>
<td>8</td>
<td>0.95</td>
<td>15.6</td>
<td>6.7</td>
<td>34 (5.3)</td>
<td>66 (10.3)</td>
<td>1.05</td>
<td>0.21</td>
<td>0.69</td>
</tr>
<tr>
<td>4</td>
<td>85</td>
<td>6</td>
<td>0.56</td>
<td>9.1</td>
<td>4.3</td>
<td>32 (2.9)</td>
<td>68 (6.2)</td>
<td>0.79</td>
<td>0.18</td>
<td>0.87</td>
</tr>
<tr>
<td>5</td>
<td>86</td>
<td>12</td>
<td>0.70</td>
<td>12.2</td>
<td>4.6</td>
<td>42 (5.1)</td>
<td>58 (7.1)</td>
<td>0.79</td>
<td>0.16</td>
<td>0.90</td>
</tr>
<tr>
<td>6</td>
<td>88</td>
<td>16</td>
<td>0.57</td>
<td>10.2</td>
<td>3.5</td>
<td>33 (3.3)</td>
<td>67 (6.8)</td>
<td>0.67</td>
<td>0.15</td>
<td>0.80</td>
</tr>
<tr>
<td>7</td>
<td>105</td>
<td>12</td>
<td>1.63</td>
<td>25.5</td>
<td>14.0</td>
<td>38 (9.6)</td>
<td>62 (15.6)</td>
<td>0.71</td>
<td>0.14</td>
<td>1.13</td>
</tr>
<tr>
<td>8</td>
<td>140</td>
<td>16</td>
<td>0.77</td>
<td>11.5</td>
<td>7.0</td>
<td>30 (3.5)</td>
<td>70 (8.0)</td>
<td>0.60</td>
<td>0.07</td>
<td>1.28</td>
</tr>
<tr>
<td>9</td>
<td>99</td>
<td>18</td>
<td>0.77</td>
<td>12.0</td>
<td>6.5</td>
<td>38 (4.5)</td>
<td>62 (7.4)</td>
<td>0.56</td>
<td>0.15</td>
<td>1.30</td>
</tr>
<tr>
<td>10</td>
<td>95</td>
<td>20</td>
<td>1.08</td>
<td>16.5</td>
<td>9.4</td>
<td>33 (5.4)</td>
<td>67 (11.1)</td>
<td>0.44</td>
<td>0.24</td>
<td>1.23</td>
</tr>
<tr>
<td>11</td>
<td>103</td>
<td>25</td>
<td>0.75</td>
<td>11.8</td>
<td>6.2</td>
<td>37 (4.3)</td>
<td>63 (7.5)</td>
<td>0.46</td>
<td>0.25</td>
<td>1.29</td>
</tr>
</tbody>
</table>

CF = Coarse fragments; ASV = Actual soil volume

Content varied from 0.44 (profile 10) to 1.18 tonnes m$^{-3}$ (profiles 1 and 2) while silt ranged from 0.07 to 0.25 tonnes m$^{-3}$. The clay varied between 0.5 to 1.3 tonnes m$^{-3}$.

**Relationship among soil properties**

Regression with data on nine soil profiles (excluding profile 3 and 9) highlighted that $\text{ASV} = -0.091 + 23.9 \times \text{depth} - 0.99 \times \text{coarse fragments} - 0.98 \times \text{porespace}$ (adjusted $R^2 = 0.999$). Data (Table 1) indicated varied ASV between profiles 1 and 7 (difference being 34%) although with similar depth because of differences in proportion of gravel and pore space. This kind of relation gives a further clue as to how ASV can influence the available water capacity (AWC), which drives latex flow. Previously, Rao and Jessy (2007) identified ‘soil water availability factor’ in factor analysis, which was highly influenced by depth (positively) and coarse fragments (negatively), while analyzing the impact of effective soil volume on growth and yield of rubber. Similarly, regression of AWC on the scores of ‘surface area factor’ and ‘soil water availability factor’ was also significant indicating direct bearing of depth and coarse fragments on availability of water. Prior to this, Sehgal (1990) stated that AWC was directly related to coarse fragments, soil depth and mineralogy of clay. These results also meant that ASV could determine soil moisture holding and supplying capacity.

**Maps of soil properties**

Various maps generated for RRS farm are presented in Fig. 2 and 3. An examination showed a rectangular interpolated area, which did not match exactly with boundary line. It was because the interpolation did not start from the origin of map rather it was from the extreme profile location on X and Y axes. However, majority of farm area was covered and is shown in maps. Slope map (Fig. 2) depicted three slope classes namely 5.1-10.0, 10.1-15.0 and 15.1-25.0% slope and their distribution in the study area. Similarly, depth map (Fig. 2) showed four classes, viz. 0.51 to 0.75, 0.76 to 1.00, 1.01 to 1.50 and >1.51 m depth. Four classes of coarse fragments and ASV expressed in m$^3$ assigned to the member soils are shown in Fig. 3. In these two cases the number and range of classes was decided arbitrarily as there was no suggested classification available based on weighted average.

The maps highlighted variability in the themes selected even in small area of 40 ha because of topography. Slope map
helps in assessing the land and to take measures of conservation of soil and moisture in high slope areas of farm as this part of north Kerala experiences dry period (>5 months) although average rainfall is up to 3500 mm. It is necessary because of rubber latex flow is directly related to soil moisture content and conservation of moisture helps in realizing better latex yield during drier months. Anyway, map of ASV is altogether a different idea and it is expected to help in effective soil management in terms of fertilizer and irrigation water management not only for rubber but other plantations crops too grown in this kind of terrain.

**Predictability of interpolated maps**

The model was tested for predictability using data on two soil profiles (3 and 9), which were not included in the model. There were over and under estimations as shown by the results (Table 2), though with varied levels. However, predictions of almost all features are probably acceptable because there is no cut off limit of error. In addition to that regression analysis already proved the absolute dependence of ASV on depth, coarse fragments and pore space. With the system error of 15 m in GPS readings and coarse resolution of DEM (90 m), the error in prediction is probably tolerable. In addition to that, many soils are described with a range of values, for example, Class D of slope (5.1 - 10 % of slope), the range can take care of these errors. That is, both actual and predicted slope for profiles 3 and 9 belonged to same class (D and F classes, respectively). Predictions of depth and coarse fragments were good because of only 11% error. Moreover, actual and predicted values of depth fall in ‘moderately deep’ class, corresponding to 0.76 - 1.0 m of depth thus ignoring the effect of error in prediction. With regards to ASV, the predictability of 81% is fairly good in this natural system of landscape. In addition to that there are no standards to describe ASV *per se* and however, scale factor also matters in the predictability of model (Thompson *et al.*, 2006).

Although there are other interpolators, IDW was selected in the present study because the predicted values are within the range of minimum and maximum values unlike another interpolator like krigging where predicted values could be lesser or higher than minimum and maximum values of a given attribute. In addition to that, there is no restriction on sample size unlike krigging where data on a minimum of 50-100 points are needed for better interpretation (Kravchenko, 2003). According to Kravchenko (2003), IDW is recommended to be used for small data sets for which variogram parameters are not known and for data sets with large distances between the grid points. Thus in the present study, the IDW was used to obtain a model with low sampling intensity.

Soil-landscape modeling has been successfully applied to predict soil variability at the site or hill slope scale, commonly focusing on study areas less than 100 ha in size (Moore *et al.*, 1993a). The results of present study also comprehended that soil-landscape modeling was a dependable tool to predict soil variability even in small areas with acceptable error. The inference from the results of present study demonstrated that generation of maps with less number of samplings was possible with reasonably good predictability.

Soil-landscape model was found to be successful in predicting soil properties with reasonably good accuracy. The present study indicated that DEM of SRTM is useful in visualization of terrain even in small area like 40 ha, which helps in reconnaissance survey and stratification for survey and

<table>
<thead>
<tr>
<th>Feature</th>
<th>Actual P3</th>
<th>Predicted P9</th>
<th>Difference (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Slope (%)</td>
<td>8</td>
<td>18</td>
<td>15.8 +18 -12</td>
</tr>
<tr>
<td>Depth (m)</td>
<td>0.95</td>
<td>0.77</td>
<td>0.8 +6 +5</td>
</tr>
<tr>
<td>Coarse fragments (m³)</td>
<td>5.3</td>
<td>4.5</td>
<td>5.9 +11 0</td>
</tr>
<tr>
<td>Actual soil volume (m³)</td>
<td>10.3</td>
<td>7.4</td>
<td>12.1 +8 +19</td>
</tr>
</tbody>
</table>

P3 = Soil profile No. 3; P9 = Soil profile No. 9
mapping purposes. When site specific nutrient management is being advocated for efficient utilization of natural resources, information about landscape attributes particularly in undulated terrains adds more to management. Moreover, the resources are freely available and thus can be put into use with much lesser costs. The results of present study in terms of intensity of soil sampling and predictability of resultant model are encouraging as only one profile per 4.44 ha was the sampling intensity. This technique can be extended to initiate mapping of various themes in other rubber growing farms in this region of India because of commonalities like in parent material, climate and human activity etc. though not in topography.

Further research is needed with regards to landform segmentation and rubber performance as the physiographic setting of rubber growing regions demand such procedures. Precision farming does not always mean use of sophisticated equipments guided by sensors and using digital maps based on GIS tools but it essentially means use of information precisely. Hence for this farm or similar, these kinds of maps are of definite help in precise plantation management.

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REFERENCES


