Spatial variability of soil color parameters and soil properties in an alluvial soil

Fevzi AKBAS

Soil, Water and Desertification Research Institute Konya, Turkey.

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Understanding of spatial variability of soil properties provides the factors and processes controlling their potential in agricultural production. The objectives of this study were to analyze spatial structure of soil properties and soil color parameters ($L^*$, $a^*$, $b^*$) in an alluvial field (45 ha) under different crop patterns, and to map soil properties using geostatistical methods. A geostatistical sampling scheme was adopted, and 188 soil samples were taken from topsoil (0-20 cm) and subsoil (20-40 cm). Soil color value $b^*$ showed the lowest variation ($CV = 6.4\%$ for topsoil and $CV = 6.1\%$ for subsoil) between soil color parameters. Available Phosphorus showed the highest variation ($CV = 64.6\%$ for topsoil and $CV = 52.4\%$ for subsoil). Geostatistical range varied from 114 m (available phosphorus) to 633 m (EC) in topsoil. Soil pH had the shortest (72 m), and CaCO$_3$ had the longest range value (612 m) in subsoil. Map of CaCO$_3$ content visually correlation with lightness ($L^*$) map in both depths but maps of the organic matter did not show visual correlation with maps of $L^*$ in both depths. Organic matter maps can be used for site specific N application because OM to some extent characterizing potential N-supplying capacity could be used as reference for N fertilizer recommendation.

Key words: Geostatistics, semivariogram, kriging, soil color.

INTRODUCTION

Different parent materials and topographies cause spatial variations, but variation in soil properties is also a result of a number of long-term and short term soil management strategies. Understanding the distribution of soil properties in the field scale is essential in refining agricultural management practices (McBratney and Pringle, 1999) while minimizing environmental damage. Color is one of the most apparent and most significant characteristics of soil, consistently used as a definitive criterion in the identification, classification and separation of soil (Sanchez-Maranon et al., 2004; Bhavanarayana, 2001). Because color is easily perceived in the field and is related to other soil properties, it has often been used as a rapid assessment indicator of such thing as drainage class, soil classification, and soil organic carbon which is affected to usage of variable rate fertilizer, pesticides application (Konen et al., 2003; Barrett, 2002).

Properties such as soil organic carbon content, iron content, soil water content, and texture have been shown to have a good correlation with soil color. Soils with dark
surface horizons are generally linked with high organic matter content, classifying them as fertile and suitable for plant growth. Dark brown and black soils are also thought to contain high level of nitrogen, have good aeration and drainage, and pose low erosion risk. Generally, the opposite is thought of light colored soil. The color of iron containing soil minerals that undergo oxidation and reduction reactions can provide useful information on the hydrologic condition of soil (Viscarra et al., 1999).

Most studies on soil color employed the Munsell color system because of its ease of use, ready availability, and historical importance to soil science. However, this method is semi quantitative, because it allows a subjective match of soil samples to the Munsell color chips (Konen et al., 2003; Barrett, 2002). Newer color systems, like those created by the Commission Internationale d’Enclairage (CIE) may be better suited to represent a uniform color space, that is, a color space where the Euclidean differences between colors are equivalent to the human perceptions of those differences (Melville and Atkinson, 1985; Scheinost and Schwertmann, 1999). Barrett (2002) used spectrophotometer to quantify soil color in situ and reported that spectrophotometer provided a higher degree of precision. Some researcher used soil CIELAB color parameter to represent soil color and reported relationships between soil color parameter and soil properties (Sánchez-Marañón, 1997; Konen et al., 2003; Gunal et al., 2008).

Spatial distribution of soil properties is not uniform. This irregular distribution of soil characteristics, such as nutrient availability, organic content, and mineral content, implicitly reflects the processes that occur within the larger ecosystem (Corstanje et al., 2006). The geostatistical approach treats soil properties as continuous variables and models, these as the most likely outcomes of random processes (Webster and Oliver, 2007), which allows random variation in soil properties to be formulated mathematically. Besides to this basic definition, Geostatistics is practically concerned with detecting, estimating and mapping the spatial patterns of regional variables, and uses point information for interpolation. Semivariogram is the core of geostatistical studies and this instrument distinguishes variation in measurements separated by given distances (Goovaerts, 1997; Isaaks and Srivastava, 1989; Rossi et al., 1992). Semivariogram models provide the necessary information for kriging, which provides the best linear unbiased prediction at un-sampled locations. In practice, kriging is often a precursor to management decisions (Lark and Ferguson, 2004). Geostatistics have been used to estimate soil physical (Jung et al., 2006; Iqbal et al., 2005), biological, and ecological properties (Rochette et al., 1991; Rossi et al., 1992; Gaston et al., 2001). Some work has optimized sampling strategies (Buscaglia and Varco, 2003; Ruffo et al., 2005).

Site-specific management zones as described by Fleming et al. (2004) and Khosla et al. (2002) were delineated from the variability in color observed in bare soil imagery of conventionally tilled field. The color of bare soil surface is largely governed by soil organic matter and moisture. Fleming et al. (2004) used soil color with farmer experience one of the methods delineating management zones in two center-pivot irrigated fields. They found that this methods promising in the future application.

In agricultural land, to reduce the variability in yield and to improve crop quality, variable rate technology needed. In addition to improvement of crop yield efficiency, economical issues and environmental concerns has necessitated the introduction of variable rate technology. Variable rate technology (site specific recommendations) is demanded for the determination of spatial variability precisely on farm level. The objectives of this study were to: (i) quantify the spatial variability and the pattern of soil properties including soil color parameters and (ii) generate maps for the spatial distribution of these variables to manage agricultural inputs.

**MATERIALS AND METHODS**

**Description of the study area**

The study site is recently consolidated area and located in 56 km north east of the Tokat province within the middle Black Sea region of Turkey (40° 28' 41"N, 36° 59' 25" E). Study area is located between Kelkit River and Canik Mountains. The field is relatively flat; having slope of 1 to 2% and a small creek called Fatli encircles the eastern border of the study area. Coarse particles and gravels found at 50 cm of the soil profiles in the middle of the study area, indicating that this small creek probably changed its bed several times in the past. The soils studied were classified as Vertic Haplustepts (Soil Survey Staff, 1999) based on a cambic B horizon and vertic properties observed during sampling.

The mean annual precipitation and air temperature are 456.4 mm and 12.3°C, respectively. Land leveling and consolidation operations were completed in the study area during 1999 and 2000 growing seasons. A small ridge in the middle of the field was also leveled during this operation. The rotation of wheat, sugar beet, maize (second crop), and alfalfa has been applied for a long time in the field. At the sampling time, some portions of the study area had been planted with winter wheat, sugar beet, and alfalfa, and rest of the field was prepared for tomato production (Figure 1). In wheat and sugar beet production, diammonium phosphate (DAP) and ammonium nitrate (AN) as a base fertilizer, and urea as a top fertilizer were used. DAP and urea fertilizers were also commonly used for tomato production as a source of P and N in the study area.

**Sampling design and analysis**

The sampling area is about 54 ha, and boundary of area is given in Figure 1. Systematic grid sampling was applied in 100 to 100 m grid cells. Soil samples were collected from upper nodes of each grid in May, 2005. At the grid intersection points, 44 main sampling points were created in 100 to 100 m grid design. In order to model short range variability of soil attributes, ten fine- transects with 2, 5, 10, 25 and 50 m intervals were sampled. The fine transects were located regularly in the north-south and east-west directions,
Soil samples were collected at two depths (topsoil, 0-20 cm and subsoil, 20-40 cm) at 94 sampling sites, and the total number of soil samples was 188 (Figure 1).

The texture of <2 mm fraction of each sample (% sand, % silt and % clay) was determined by the Bouyoucos hydrometer method (Gee and Bouder, 1986). Electrical conductivity and pH of soils were measured 1:2.5 soil water suspension (Hendershot et al., 1993). Organic matter was measured by the Walkley Black method (Nelson and Sommers, 1982), and calcium carbonate content was determined with a pressure calcimeter (Nelson, 1982). Total N was measured Kjeldal method (Bremner, 1965), and available phosphorus was determined with Olsen et al. (1954).

Soil color is commonly and widely measured using Munsell soil color chart (Munsell Color Company, 1994) Because of variation in light sources and surface properties soil color chips and soil, observers perceive varied and assignment of soil color. The limitations can be eliminated by using a colorimeter, which is an instrument capable of providing both accurate and precise soil color data (Torrent and Barron, 1993).

Colorimeters have numerous advantages for quantifying soil color properties. The technique is non-destructive and further analyses can be run on the same sample. The instrument is portable and can be taken to the field. Color parameter may be determined on both dry and moist samples in seconds. Sample preparation is minimal and the methods is more consistent, accurate, and precise than color quantification by the human eye using Munsell soil color books or color chart developed specifically for estimating soil organic carbon or soil OM concentrations (Konen et al., 2003). Colors are specified in CIELAB color space using three coordinates: L* (similar to munsell value), a* (denoting hue on the redgreen axis), and b* (which denotes hue on the yellowblue axis). The L* axis represent lightness ranging from no reflection for black (L=0) to perfect diffuse reflection for white (L=100). The a* axis is the redness ranging from negative values for green to positive values for red, and b* axis is the yellowness ranging from negative values for blue and positive values for yellow (Melville and Atkinson, 1985).

The colors of soil samples were measured with the CR300 Chroma Meter (Minolta, Osaka, Japan) and spectral reflectance was determined over the 400 to 700 nm range. We calibrated the chroma meter with a standard white plate (Minolta) at the start of each sample set run. Soils were ground and passed through a 2 mm sieve, and placed in a Petri dish to provide minimum of a 1 cm thickness, and five spectra from different locations were averaged from each sample.

**Data analysis**

Descriptive statistics was conducted on physical and chemical properties of soils studied. Exploratory data analysis was made.
calculating minimum, maximum, arithmetic mean, standard deviation, coefficient of variation (CV), skewness, and kurtosis for each variable. Classical statistic was conducted with SPSS 10.0 statistical software (SPSS, 2000). The spatial structure of variables was characterized using experimental semivariogram, expressed as:

$$\lambda(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [z(x_i) - z(x_i + h)]^2$$  \hspace{1cm} (1)

where, $\lambda(h)$ is the experimental semivariogram value at the distance interval $h$; $N(h)$ is number of sample value pairs within the distance interval $h$; $z(x_i)$ and $z(x_i + h)$ are the sample values at two points by the distance interval $h$ (Isaaks and Srivastava, 1989).

Nugget effect expressed as (Co/Co+C), where Co is nugget variance and Co+C is sill, quantifies spatial dependency of the soil properties (Cambardella et al., 1994). Anisotropic semivariograms did not show any differences in spatial dependence based on directions, hence isotropic semivariograms were considered in further analyses. The parameters of model: nugget semivariance, range, and sill were determined. Nugget semivariance is the variance at zero distance; sill is the semivariance value at which the variogram levels off; and range is the distance at which one variable become spatially independent or the lag distance at which the semivariogram reaches the sill value. Modeling of isotropic experimental semivariogram was performed with GS+ (Version 7) statistical software (Gamma Design Software, 2004), and a maximum lag distance of 700 m were applied in experimental semivariogram modeling. Since the use of log-transformed data slightly affected the kriging predictions, untransformed data were used in predictions (except available phosphorus in subsoil). The best fit model selection for experimental semivariogram was done using their respective isotropic semivariogram models (Isaaks and Srivastava, 1989).

Ordinary kriging method assumes that the data set has a stationary variance but also a non-stationary mean within the study area. The color of samples was between 31.31 and 45.73 for L* in topsoil. Mean color deviation, coefficient of variation (CV), skewness, and kurtosis for each variable. Classical statistic was conducted with SPSS 10.0 statistical software (ESRI, 2001). The mean absolute error (MAE) and the mean squared error (MSE) were calculated to compare prediction. The MAE is a measure of the sum of the squared residuals,

$$MSE = \frac{1}{n} \sum_{i=1}^{n} [z(x_i) - \hat{z}(x_i)]^2$$  \hspace{1cm} (5)

is the difference at any point which gives an indication of the magnitude of differences such that small MSE values indicate more accurate prediction, point-by-point. Another measure of effectiveness of prediction is the $G$ value (goodness of prediction),

$$G = \left[1 - \frac{1}{n} \sum_{i=1}^{n} [z(x_i) - \hat{z}(x_i)]^2 / \sum_{i=1}^{n} [z(x_i) - \bar{z}]^2 \right] * 100$$  \hspace{1cm} (6)

where $\bar{z}$ is the sample mean. When the $G$ value equal the 100% indicates perfect prediction, negative values indicates the predictions are less reliable (Schloeder et al., 2001).

RESULTS AND DISCUSSION

Descriptive statistics

The descriptive statistics for soil parameters in the study area are presented in Table 1. The means of soil variables were similar in two depths suggested that surface soils (0-20 cm) of the study area generally look like deeper part (20-40 cm). The soils were clayey in texture, the mean clay content 42.87 and 42.90% in topsoil and in subsoil, respectively. Average calcium carbonate content of the topsoil was 8.77%, which was slightly lower than that of subsoil (9.20%). Organic matter (OM) content of soils investigated was low due to the intensive tillage by moldboard, and absence of manure and plant residue additions. OM content of topsoil (1.79%) was higher than that of subsoil (1.25%). The pH was similar in top and subsoil, 7.96 and 8.08, respectively (Ozgoz et al., 2009), and soluble salt content was low at both depths (Table 1). Total N (TN) of subsoil is slightly lower than topsoil. Available phosphorus (AP) is almost 3 times higher in topsoil than in subsoil. This indicates that excessive phosphorus fertilization is subject to surface soil of study area. The color of samples was between 3.99 and 5.56 for a*, between 12.75 and 16.75 for b*, and between 31.31 and 45.73 for L* in topsoil. Mean color values of a*, b*, and L* were slightly higher in subsoil.

Majority of the soil properties had positive skewness and kurtosis values in both depths. All variable except sand, EC and AP in topsoil were slightly skewed (skewness < 1). In subsoil sand, CaCO₃, and AP had skewness value higher than 1 and other soil variables were slightly skewed.

Soil pH had the lowest CV (1.3%) in topsoil and subsoil. While silt, L*, a* and b* had low CV values (6.4 to 12.1%), clay, sand, CaCO₃, OM, EC and TN had medium CV values in topsoil (21.8 to 32.6%). AP had the highest CV (64.6%) and ranged from 5.26 to 105.25 mg kg⁻¹ in
Correlation coefficient between CaCO3 and soil color with calcium carbonate in topsoil and subsoil (P<0.01) was found between soil color parameters, L*, a*, and b* between the selected soil properties. Strong correlation topsoil. Table 2 shows the degree of correlations slightly higher variability (higher CV) in subsoil than AP had higher CV in topsoil while OM and total N had and subsoil. Management related soil properties EC and soil properties were in the same variability class in topsoil CV values which were 38 and 36%, respectively. Other to high variability in subsoil compared to topsoil based on surface soil (Table 1). Sand and OM shifted from medium to high variability in subsoil compared to topsoil based on CV values which were 38 and 36%, respectively. Other soil properties were in the same variability class in topsoil and subsoil. Management related soil properties EC and AP had higher CV in topsoil while OM and total N had slightly higher variability (higher CV) in subsoil than topsoil. Table 2 shows the degree of correlations between the selected soil properties. Strong correlation was found between soil color parameters, L*, a*, and b* with calcium carbonate in topsoil and subsoil (P<0.01). Correlation coefficient between CaCO3 and soil color parameter (L*, a*, b*) were higher in subsoil compared to topsoil. Soil color b* values inversely correlated with OM (r = -0.31**, P<0.01) in subsoil. Correlation coefficient between EC with L* was negative in subsoil and there was negative correlation between EC and a* in topsoil. In both soil depth EC was inversely correlated with b* (P<0.01). Soil color parameter L* and a* were not significantly correlated with clay and sand. But clay and b* negatively correlated in topsoil and subsoil (r = -0.42** and r = -0.34**) and sand had positive correlation with b* in topsoil (P<0.01).

Geostatistical analysis

Table 3 lists the best-fitted isotropic semivariogram model parameters and some spatial structural indices of soil properties in topsoil and subsoil. The directional semivariograms calculated at the angles of 0° (N - S), 45° (NE - SW), 90° (E - W), and 135° (SE - NW) for the measured variables indicated no distinct anisotropy. Therefore, omni-directional semivariograms were modeled to determine the spatially dependent variance within the research area. Clay, sand, CaCO3 and b* were
Table 3. Geostatistical parameters of soil properties in 0-20 cm and 20-40 cm soil depths.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Clay %</th>
<th>Silt %</th>
<th>Sand %</th>
<th>CaCO$_3$ %</th>
<th>Org. Mat. %</th>
<th>pH</th>
<th>EC dSm$^{-1}$</th>
<th>AP mg kg$^{-1}$</th>
<th>TN (%)</th>
<th>L*</th>
<th>a*</th>
<th>b*</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Surface soil (0-20 cm)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(C$_o$)</td>
<td>12.5</td>
<td>6.92</td>
<td>3.5</td>
<td>1.5</td>
<td>0.1019</td>
<td>0.00575</td>
<td>18510</td>
<td>0.217</td>
<td>0.00019</td>
<td>2.49</td>
<td>0.0443</td>
<td>0.227</td>
</tr>
<tr>
<td>(C$_o$+C)</td>
<td>102.6</td>
<td>14.37</td>
<td>88.8</td>
<td>7.18</td>
<td>0.2598</td>
<td>0.0116</td>
<td>39570</td>
<td>0.435</td>
<td>0.00038</td>
<td>6.557</td>
<td>0.1196</td>
<td>0.959</td>
</tr>
<tr>
<td>Range(m)</td>
<td>379</td>
<td>297</td>
<td>370</td>
<td>486</td>
<td>252</td>
<td>358</td>
<td>633</td>
<td>114</td>
<td>135</td>
<td>219</td>
<td>501</td>
<td>259</td>
</tr>
<tr>
<td>(C$_o$)/(C$_o$+C)</td>
<td>12.1</td>
<td>48.1</td>
<td>3.9</td>
<td>20.9</td>
<td>39.2</td>
<td>49.6</td>
<td>46.8</td>
<td>49.8</td>
<td>50</td>
<td>37.9</td>
<td>37</td>
<td>23.7</td>
</tr>
<tr>
<td>$r^2$</td>
<td>0.84</td>
<td>0.80</td>
<td>0.80</td>
<td>0.84</td>
<td>0.79</td>
<td>0.77</td>
<td>0.68</td>
<td>0.45</td>
<td>0.54</td>
<td>0.80</td>
<td>0.85</td>
<td>0.81</td>
</tr>
<tr>
<td>RSS$^3$</td>
<td>1606</td>
<td>14</td>
<td>1991</td>
<td>8.68</td>
<td>0.006</td>
<td>8.5x10$^{-4}$</td>
<td>2.2x10$^{-8}$</td>
<td>0.03</td>
<td>1.2x10$^{-8}$</td>
<td>3.56</td>
<td>0.001</td>
<td>0.16</td>
</tr>
<tr>
<td>SC$^2$</td>
<td>S</td>
<td>M</td>
<td>S</td>
<td>S</td>
<td>M</td>
<td>M</td>
<td>M</td>
<td>M</td>
<td>M</td>
<td>M</td>
<td>M</td>
<td>M</td>
</tr>
<tr>
<td>MAE</td>
<td>3.74</td>
<td>2.76</td>
<td>2.96</td>
<td>1.04</td>
<td>0.33</td>
<td>0.08</td>
<td>0.13</td>
<td>15.89</td>
<td>0.01</td>
<td>2.01</td>
<td>0.21</td>
<td>0.60</td>
</tr>
<tr>
<td>MSE</td>
<td>27.11</td>
<td>11.83</td>
<td>20.36</td>
<td>2.02</td>
<td>0.20</td>
<td>0.01</td>
<td>0.03</td>
<td>453.8</td>
<td>0.0003</td>
<td>6.54</td>
<td>0.07</td>
<td>0.66</td>
</tr>
<tr>
<td>G</td>
<td>69</td>
<td>13</td>
<td>72</td>
<td>66</td>
<td>15</td>
<td>18</td>
<td>14</td>
<td>-1</td>
<td>6</td>
<td>11</td>
<td>58</td>
<td>26</td>
</tr>
<tr>
<td><strong>Subsurface soil (20-40 cm)</strong></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>(C$_o$)</td>
<td>32.8</td>
<td>7.29</td>
<td>22.8</td>
<td>0.68</td>
<td>0.0357</td>
<td>0.00245</td>
<td>2090</td>
<td>0.052</td>
<td>0.00028</td>
<td>2.67</td>
<td>0.0369</td>
<td>0.263</td>
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<tr>
<td>(C$_o$+C)</td>
<td>120.1</td>
<td>21.15</td>
<td>124</td>
<td>12.3</td>
<td>0.207</td>
<td>0.0117</td>
<td>5661</td>
<td>0.242</td>
<td>0.00057</td>
<td>10.63</td>
<td>0.1725</td>
<td>0.845</td>
</tr>
<tr>
<td>Range(m)</td>
<td>402</td>
<td>516</td>
<td>321</td>
<td>612</td>
<td>129</td>
<td>72</td>
<td>213</td>
<td>75</td>
<td>162</td>
<td>183</td>
<td>515</td>
<td>106</td>
</tr>
<tr>
<td>(C$_o$)/(C$_o$+C)</td>
<td>27.3</td>
<td>34.4</td>
<td>18.3</td>
<td>5.5</td>
<td>17.2</td>
<td>20.9</td>
<td>37.5</td>
<td>21.5</td>
<td>49.1</td>
<td>25.1</td>
<td>21.4</td>
<td>31.1</td>
</tr>
<tr>
<td>$r^2$</td>
<td>0.82</td>
<td>0.89</td>
<td>0.68</td>
<td>0.95</td>
<td>0.69</td>
<td>0.50</td>
<td>0.70</td>
<td>0.87</td>
<td>0.41</td>
<td>0.73</td>
<td>0.82</td>
<td>0.86</td>
</tr>
<tr>
<td>RSS$^3$</td>
<td>2567</td>
<td>26.4</td>
<td>5115</td>
<td>13.8</td>
<td>9.8x10$^{-3}$</td>
<td>2.3x10$^{-5}$</td>
<td>3.9x10$^{-8}$</td>
<td>2.7x10$^{-3}$</td>
<td>6.9x10$^{-8}$</td>
<td>15.1</td>
<td>5.3x10$^{-3}$</td>
<td>0.09</td>
</tr>
<tr>
<td>SC$^2$</td>
<td>M</td>
<td>M</td>
<td>S</td>
<td>S</td>
<td>S</td>
<td>S</td>
<td>S</td>
<td>S</td>
<td>M</td>
<td>M</td>
<td>M</td>
<td>M</td>
</tr>
<tr>
<td>MAE$^4$</td>
<td>5.51</td>
<td>2.96</td>
<td>4.64</td>
<td>1.20</td>
<td>0.30</td>
<td>0.08</td>
<td>0.05</td>
<td>4.48</td>
<td>0.02</td>
<td>2.18</td>
<td>0.229</td>
<td>0.269</td>
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<tr>
<td>MSE$^4$</td>
<td>62.48</td>
<td>15.99</td>
<td>54.22</td>
<td>2.90</td>
<td>0.14</td>
<td>0.01</td>
<td>0.005</td>
<td>34.73</td>
<td>0.001</td>
<td>8.03</td>
<td>0.09</td>
<td>0.82</td>
</tr>
<tr>
<td>G$^4$</td>
<td>46</td>
<td>19</td>
<td>50</td>
<td>69</td>
<td>28</td>
<td>6</td>
<td>13</td>
<td>7</td>
<td>-7</td>
<td>2</td>
<td>39</td>
<td>6</td>
</tr>
</tbody>
</table>

1 log transformed data were used, 2 SC: Spatial class; S: strong; M: moderate, 3 RSS: Residual sum of squares, 4 MAE: Mean absolute error, MSE: Mean squared error; G: Goodness of prediction as defined by Schloeder et al. (2001).

The nugget/sill ratio ($C_o/(C_o+Co)$) can be regarded as a criterion to classify the spatial dependency of soil properties. A variable has strong spatial dependency if the ratio less than 25%, moderate spatial dependency if the nugget/sill is between 25 and 75%, and weak spatial dependency for nugget/sill are greater than 75% (Cambardella et al., 1994). The resulting semivariograms indicated the existence of moderate to strong spatial dependence for all soil properties for each depth (Table 3). Clay, sand, CaCO$_3$ and $b^*$ were strongly spatially dependent, with the nugget/sill ratio ranging from 3.9 to 23.7% in topsoil. Silt, OM, pH, EC, AP, TN, L* and a* were moderately spatially dependent and nugget/sill values varied between 37 and 49.6% in topsoil. While sand, CaCO$_3$, OM, pH and a* were strongly spatially dependent, the remaining soil properties were modeled quite well with spherical model, whereas the remaining properties were modeled with exponential models in topsoil. Spherical model were used for clay, sand, a* and b* in topsoil while exponential model was provided the best fit for other soil properties in subsoil. The nugget/sill ratio ($C_o/(C_o+Co)$) can be regarded as a criterion to classify the spatial dependency of soil properties. A variable has strong spatial dependency if the ratio less than 25%, moderate spatial dependency if the nugget/sill is between 25 and 75%, and weak spatial dependency for nugget/sill are greater than 75% (Cambardella et al., 1994). The resulting semivariograms indicated the existence of moderate to strong spatial dependence for all soil properties for each depth.
moderately spatially dependent in subsoil. The spatial variability of soil properties may be affected by both intrinsic (soil formation factors such as parent material and climate) and extrinsic factors (soil management practices, such as fertilization and irrigation). In general, strong spatial dependency of soil properties can be attributed to intrinsic factors, and weak spatial dependency can be attributed to extrinsic factors (Cambardella et al., 1994). Textural components (clay and sand) and CaCO3 showed strong dependency in surface soil. When soil properties show strong spatial dependency it may indicate that the variability in these properties is controlled by intrinsic variation. Nugget/sill ratios of management related soil properties were higher in topsoil than subsoil. This was suggesting that the extrinsic factors such as fertilization, plowing and other management practices may be weakened their spatial correlation in topsoil. These soil properties were OM, pH, EC, AP, TN which showed moderate spatial dependency in topsoil. AP and TN showed highest nugget effect in topsoil and this was evidence effect of fertilizer application to the soil heterogeneity. Sampling area was a 45 ha-field and covered with four different crop patterns in about 32 production parcels (Figure 1). Various crop patterns at the time of sampling associated with different rate of nitrogen and phosphorus fertilizer usage weakened spatial correlation of AP and TN in topsoil.

Nugget variance (Co) represents variance due to measurement error or short range variability of the property which cannot be detected with the current scale of sampling. The semivariance increases as the separation distance between sample locations increases, rising to an approximately constant value called sill (Co+C). Spherical semivariogram model was used for the semivariograms of clay, sand, calcium carbonate and b* and exponential semivariogram model was used other soil properties in topsoil. Clay, sand and a* were best modeled with spherical semivariogram model and remaining properties were modeled with exponential model in subsoil.

One of the useful results that is obtained from spatial analysis is the range. This value is the approximate distance from one point to another within the field, which would be assumed to be correlated. Therefore, a small value would indicate a great amount of variability within a field. Large values indicate greater distances that the samples could be obtained and the data still be correlated. In our study, range values of all soil properties in topsoil were greater than 200 m except AP and TN. In contrast to topsoil six soil properties (OM, pH, AP, TN, L* and b*) had range values lower than 200 m in subsoil. This indicates that the mentioned soil properties were more variable in subsoil compared to the topsoil. However, with the exception of pH and AP, the range of various semivariogram models which exceeded 100 m indicated the presence of spatial structure beyond the original main grid sampling distance in the subsoil. The ranges of L* and b* decreased with depth, from 219 to 183 m in the plow layer for L* and from 259 to 106 m at deeper depth for b*. But the range values of a* were very close to each other in both depths and these range values were 501 m in topsoil and 515 m in subsoil.

Fine textured soil was found in the north and north-central where large areas within the range of 45 to 55% in clay content were common. Reversely, sandy soil were located south part of the study area. Based on contour maps patterns in Figure 2, EC, TN and AP were patchy spatial distribution in subsoil but more regular patterns and steady structures in topsoil. It is somewhat surprising that no patch distribution of EC, TN and AP was noted in this study for surface soil. It is reported that patchy distributions of soil maps was mainly controlled by random factor (Cambardella et al., 1994). The level of EC, TN and AP in surface soil is generally altered by management (fertilizer application, irrigation, plant uptake) therefore patchy distribution may indicate management effects to these properties. Some other studies reported that weak or no spatial dependency for TN (Eltaib et al., 2002; Jung et al., 2006) and for AP (Brouder et al., 2001; Han et al., 2005). Spatial distribution patterns of clay, silt, sand and CaCO3 were almost same in topsoil and subsoil.

The distribution maps of all variables are shown in Figure 2. CaCO3 content visually correlated with soil lightness (L*). Significant correlation existed between lightness (L*) and CaCO3 in both depth (Table 2). As reported in previous studies (Sánchez-Marañón et al., 1997; Spielvogel et al., 2004) greater lightness values are expected for the soils with high CaCO3 content. High calcium carbonate occurred in the northern area and low calcium carbonate in the southern. Northern part of the study area had calcium carbonate over 10% (up to 18.41) and lightness values were also higher than other parts. The corresponding L* values at this part of the study area were 45.7 in topsoil and 49.3 in subsoil.

Maps of the organic matter did not show visual correlation with maps of L* at both depths. Organic matter and soil lightness were reported inversely correlated (Viscarra Rossel et al., 2006; Sánchez-Marañón et al., 1997) but no significant correlation was also detected between OM and L* in this study (Table 2). Similar to L* (lightness) the a* values (red-green axis) the northern part of the study area higher a* values meant that soils of this region was slightly more redder. Coarse textured area (low in clay content high in sand content) had higher b* values (yellow blue axis) it meant that the soils of this area were slightly more yellowish. However, the difference between maximum and minimum values of soil color parameters a* and b* were very narrow indicating soils were homogeneous in their redness and yellowness. This can be explained by the extent of the study area. The test area is relatively small (45 ha) for observing distinct parent material accordingly wide range color differences in soils of the study area were not
Figure 2. Spatial distribution maps of soil properties (L*, a*, b*, clay, silt, sand, CaCO3, OM, pH, EC, AP, TN).
detected. For the first depth (0-20 cm) CaCO3 ranged from 4.74 to 15.50%, whereas in second depth (20-40 cm), CaCO3 ranged 4.37 to 18.41%, indicating similar range of calcium carbonate content in the study area. According to correlation coefficients given in Table 2, CaCO3 content and soil color a* values positively correlated (P<0.01); in addition, these properties exhibited largest and similar geostatistical range values in both depth, indicating significant spatial structure extended over 500 m (Table 3). The spatial distribution of CaCO3 and soil color a* value generally show a gradient north to south, with CaCO3 elevated areas on the north edge of the study area (Figure 2). Gunal et al. (2008) reported strong relationship between CaCO3 and soil color a* value, and interpreted that the rubification process that yielded the red color in soil was the result of the formation of iron oxides.

According to cross-validation results (Table 3), there were four prominent soil properties for which we obtained relatively more accurate and effective prediction based on MAE, MSE and G values in both depths. These were clay, sand, CaCO3 and soil color a* value and calculated G values of these properties were positive and a lot higher. G values of other soil properties were positive, indicating interpolated maps represented a significant improvement from the interpolation of the sample mean. G values AP in topsoil and TN in subsoil resulted in negative values which indicates prediction maps are less reliable. Schloeder et al. (2001) reported that poor interpolation results may be due to either very high nugget or very high sill-to-nugget ratios (>30%). High nugget values yielded higher predictions than real values while high sill-to-nugget ratios resulted increase prediction variances. Both were consequences of limited, high variable and weakly autocorrelated data (Schloeder et al., 2001).

Conclusion

Coefficient of variation ranged from 1.3% for pH and to almost 64.6% for soil AP in topsoil indicating the heterogeneity of soil properties. However, soil color parameters (L*, a* and b*) were much lower CV values (6.4 to 6.9%), colors of study soils seemingly homogeneous. Soil color parameters can be used to delineate soil management zones. OM, TN and AP maps showed steady spatial pattern with regular borders was very suitable variable rate fertilization to improve crop yield quality. OM and TN maps can be used for site specific N application because OM and TN to some extent characterizing potential N-supplying capacity could be used as reference for N fertilizer recommendation. Similarly, AP maps in surface soil could be used as site specific phosphorus management. Application variable rate fertilization reduces excessive usage of fertilizer and so protect environment from oversupplied nutrients in conventional farming systems.

Conflict of Interests

The author(s) have not declared any conflict of interests.

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