Proceedings of the 8th International Symposium on
Spatial Accuracy Assessment in Natural Resources and Environmental Sciences
Shanghai, P. R. China, June 25-27, 2008, pp. 294-301

Field-Scale Mapping of Soil Organic Carbon with Soil-Landscape Modeling

Feng Chen [1 +], Larry T. West [2], David E. Kissel [1], Rex Clark [3], and Wayne Adkins [1]

[1] Department of Crop & Soil Sciences, University of Georgia, USA
[2] National Soil Survey Center, USDA-NRCS, USA
[3] Department of Biological & Agricultural Engineering, University of Georgia, USA

Abstract. Predicting soil organic carbon (SOC) at a field scale plays an important role in field management practices for studies in both soil quality and carbon sequestration. Examining SOC concentration with soil-landscape relations provided an alternative technique for mapping SOC concentrations. The objectives of this study were to develop soil-landscape models for a crop field by quantifying the relationships between SOC concentration and terrain attributes derived from digital elevation models (DEMs), and to refine the models by delineating the sub-watersheds within the field. Separated soil sample sets were obtained from a 115 ha field located in the coastal plain region of Georgia for model development and model validation. The high accuracy GPS measurements over the field were obtained with a survey grade GPS system. The DEMs with 1, 2, 4, and 8 m grid sizes were created by interpolating the GPS data, and the terrain attributes were further derived from the DEMs. Correlation coefficients between SOC concentration and terrain attributes were analyzed and indicated that the topographic wetness index was the best single predictor for mapping SOC concentration. The study found that prediction of SOC concentration using the DEM with 2 m grid size yielded the best accuracy in both cases. The effects of grid sizes on the sub-watershed delineation and prediction accuracy were also discussed.

Keywords: digital elevation model, global positioning system, soil-landscape modelling, soil organic carbon, sub-watershed.

1. Introduction

The spatial distribution of soil organic carbon (SOC) concentration of surface soil is an important soil property in crop management for guiding fertilizer and chemical applications. Surface soil organic carbon (SOC) concentration affects the activities of many pesticides and herbicides, influences plant available soil water, and affects the soil's ability to adsorb plant nutrients (Dahnke and Johnson, 1990; Hance, 1988; Havlin at al., 1999). With the rising concern over global change, SOC may have its greatest influence on environmental processes at a global scale. Topsoil is a huge terrestrial reservoir of carbon as soil is the final destination of the vast majority of photosynthetic carbon fixed in the earth ecosystems (Rodriguez-Murillo, 2001; Sparling et al., 2006).

Various approaches have been conducted for mapping the soil organic carbon concentration of crop fields with remote sensing in recent years (Chen et al., 2000; Fox and Sabbagh, 2002; Ebinger et al., 2003; Fox and Metla, 2005; Chen et al., 2008). However, the main disadvantage of these approaches was the effects of field condition such as surface cover and soil water content (Chen et al., 2000). Soil properties such as soil texture and iron could also affect the prediction of SOC concentration (Ebinger et al., 2003; McCarty et al., 2002). Digital terrain attributes and the derived hydrological parameters have been used to quantitatively analyze and predict the spatial distributions of soil properties such as SOC concentration (Moore et al., 1991; Florinsky et al., 2002; Terra et al., 2004; Thompson et al., 2006). These studies revealed

[+] Corresponding author. Tel.: 1-706-542-0905; fax: 1-706-542-0914.
E-mail address: fchen@uga.edu.

ISBN: 1-84626-170-8, **ISBN13:** 978-1-84626-170-1

that the combination of topographic attributes could explain 37% to 58% of the variability in SOC content. The use of spatial statistical techniques such as Kriging could lead to better prediction of SOC concentrations (Mueller and Pierce, 2003; Terra et al., 2004).

Studies have also shown the improvement of predicting SOC concentration from terrain attributes over a site with relatively simple topography (Gessler et al., 2000) or for a whole watershed (Thompson and Kolka, 2005). The R^2 values for the developed models of predicting SOC in these studies increased up to 0.8. These previous studies suggested that prediction of SOC concentration might be improved by dividing a field into relatively smaller and simpler units and then predicting SOC concentration for those units. From observation of field topography, fields frequently have local depressional (or low spot) areas receiving runoff and crop residues during runoff events. The accumulation of SOC is also generally increased toward to the center of these depressional areas. This fact would lead us to model SOC concentration based on physical attributes of those depressional areas. A description of these physical attributes could be extracted from a DEM, and defining each depressional area extracted as a sub-watershed. The prediction of SOC concentration might be improved by examining the characteristics of the sub-watersheds. The specific objectives of this study were a) to predict SOC concentrations with terrain attributes for a crop field by delineating sub-watersheds within the field, and b) to examine the improvement of SOC prediction with sub-watershed delineation and examine the effect of grid size for prediction of SOC concentration.

2. Materials and Methods

2.1. Study area and Soil sampling

A 115 ha field located in the north-west corner of Crisp County, Georgia, was selected for this research (83°56'20.510" to 83°56'51.944" W; 32°00'16.994" to 32°01'24.675" N). The dominant soils in the field are Norfolk sand (fine, kaolinitic, thermic Typic Kandiudults) and Orangeburg sandy loam (fine-loamy, kaolinitic, thermic Typic Kandiudults) series, typical of the Georgia Coastal Plain (Figure 1). The field is gently rolling with elevations varying from 75 to 85m and slopes generally less than 5% (Figure 2). Low-elevation depressional areas may be ponded during intense rainfalls and generally have thicker and darker surface horizons than surrounding higher elevation areas. Because the movement of water and substances into a depressional area converges to the local lowest point, each of those convergent areas can be considered as a small watershed (a sub-watershed). The boundary of a sub-watershed can be determined with the digital elevation model of the field.

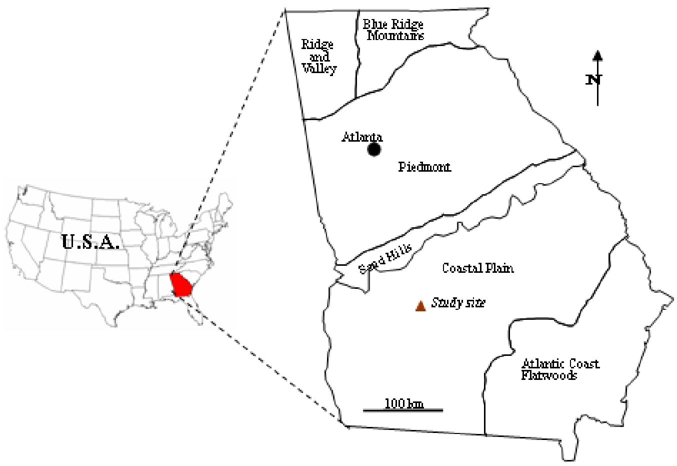

Figure 1. The location of study site and major land resource areas within the State of Georgia

A total of 88 soil samples were collected from the field. The locations of all soil samples were measured using a global positioning system (GPS) with sub-meter accuracy. Total SOC concentrations for the samples were determined with a Leco CNS analyzer (Nelson and Sommers 1996). Forty five soil samples were taken first to develop the model for mapping SOC concentration. To check the accuracy of the maps of SOC concentration, an additional forty three soil samples were taken.

Figure 2. The digital elevation model with 2 m grid size created from GPS measurement. The white spots were the locations of soil samples used for model development

2.2. Digital elevation model and terrain analysis

Elevation data for the field was collected using a dual-frequency real-time GPS with one GPS receiver serving as a stationary base station and a second unit mounted on a small tractor to record elevation and locations. The measurement was taken along transects over the whole field with a space around 10 meter apart between two transects. The accuracy of the GPS measurement was < 0.02 m in horizontal plane and < 0.05 m vertically. The measured elevation data was interpolated with ArcGIS software (ESRI Version 9.1, 2006) to generate four digital elevation models (DEMs) with grid size of 1, 2, 4, and 8 m (Figure 2).

Terrain attributes, including elevation (Z), slope gradient (S), flow accumulation (F_a), upslope flow length (F_{ul}), profile curvature (K_{pr}), plan curvature (K_{pl}), total curvature (K), and specific catchment area (A_s) (Moore et al., 1991), were derived from the DEMs. The second terrain attributes, including the topographic wetness index (TWI = $\ln(A_s / S)$) (Wilson and Gallant, 2000), the stream power index (SPI = $\ln(A_s \times S)$) (Wilson and Gallant, 2000), and the terrain characterization index (TCI = $\ln(A_s) \times K$) (Park et al., 2001), were also derived from the terrain attributes. These terrain attributes were derived for the four DEMs.

2.3. Statistical analysis and modeling

The values of the terrain attributes at the 45 sampled locations were determined by overlaying these locations on the terrain attribute grids. The correlation coefficients were examined among SOC, the terrain attributes, and the best model of predicting SOC from those terrain attributes was developed with step-wise regression analysis for each grid size. The map of SOC with 2 m grid size was created based on the prediction models for this grid size, and the accuracy of the map was evaluated based on the additional 43 soil samples collected in the second field sampling.

The sub-watersheds for each grid size were delineated using the created DEMs. Because the sub-watersheds around the field boundary were corrupted by the boundary, they were incomplete and significantly distorted by the boundary. This would modify the movement of surface water and solid substances, and therefore would affect the accumulation of SOC. In order to eliminate the effect of the field boundary, the sub-watersheds that were corrupted by the field boundary were extracted and were excluded from further analysis. The sub-watersheds completely within the field were then used to develop the prediction models of SOC concentration in different grid sizes using the soil samples from those complete sub-watersheds. The map of SOC concentration with 2 m grid size was developed for the complete sub-watersheds and the accuracy was checked using the soil samples taken from these sub-watersheds in the second field sampling.

2.4. Comparison of prediction models with different grid sizes

The effects of different grid sizes on the prediction models were examined for the models developed with 1, 2, 4, and 8 m grid sizes. These models were compared to select a possible best grid size for mapping SOC concentration at a field scale. Because a change of grid size would also cause a change of sub-watershed boundaries, the effects of sub-watershed boundary locations on SOC prediction were discussed. Finally, the effect of soil sample locations was also examined.

3. Results and Discussion

3.1. Correlations between SOC and terrain attributes and SOC prediction

The correlation coefficients among SOC concentration and terrain attributes derived from 2m grid DEM for 45 sampled locations were shown in Table 1. SOC concentration was positively related to flow accumulation, upslope flow length, profile curvature, wetness index and steam power index. SOC concentration was also negatively related to elevation, slope percent, plan curvature, total curvature, and terrain characterization index. Similar results were also observed for those derived from the DEMs with 1, 4, and 8 grid sizes. The topographic wetness index was shown to have the highest correlation coefficient with SOC concentration (Table 1). It was also true for other grid sizes. This fact suggested that accumulation of water on the landscape would result in increased SOC concentration and the topographic wetness index would be the best single predictor for mapping SOC concentration.

Table 1. Pearson correlations between SOC concentrations and terrain attributes at the samples locations

	SOC	Z	S	Fa	Ful	Kpl	Kpr	K	TWI	SPI
Z	-0.37									
S	-0.43	ns								
Fa	0.37	ns	ns							
Ful	0.54	-0.55	ns	0.67						
Kpl	-0.45	0.34	ns	-0.75	-0.71					
Kpr	0.33	ns	ns	0.58	0.47	-0.56				
K	-0.45	0.36	ns	-0.76	-0.68	0.90	-0.87			
TWI	0.65	-0.31	-0.40	0.57	0.82	-0.61	0.34	-0.54		
SPI	0.38	-0.52	ns	0.54	0.87	-0.68	0.46	-0.65	0.69	
TCI	-0.42	ns	ns	-0.93	-0.66	0.85	-0.74	0.90	-0.50	-0.54

Z: elevation, S: slope, Fa: flow accumulation, Ful: upslope flow length, Kpl: plan curvature, Kpr: profile curvature, K: total curvature, TWI: topographic wetness index, SPI: stream power index, TCI: terrain characterization index, ns: Not significant at $P < 0.05$

The best regression equation for predicting SOC concentration with a 2 m grid size included terrain attributes of elevation, slope gradient, and stream power index. The equation was listed as follows:

$$SOC\ \% = 6.615 - 0.084\ Z + 1.196\ \exp(-S) + 0.103\ SPI \quad (1)$$

The R^2 and RMSE values for the model were 0.58 and 0.315, respectively. The map of SOC concentration for the field was developed with the prediction equation. With the additional 43 samples obtained in the second field sampling, the validation of the SOC map with a linear regression analysis between the measured and the predicted surface SOC concentrations gave r^2 and RMSE values of 0.41 and 0.285, respectively. The linear regression was expressed as follows:

$$SOC_{Measured} = 0.890\ SOC_{Predicted} \quad (2)$$

3.2. Improving SOC mapping with delineation of sub-watershed

A sub-watershed is an area with a local depression or lowest center for accumulation of water and other material. We noticed that the field boundary corrupted the natural boundaries of sub-watershed. This corruption resulted in incomplete sub-watersheds around the field boundary. Therefore, the accumulation of water and SOC concentration for the corrupted sub-watersheds was interrupted, and this would further affect the prediction of SOC concentration from terrain attributes. To examine this influence, the sub-watersheds in the field were constructed using the DEMs, and the sub-watersheds intersected by the field boundary were removed, keeping only those completely within the field (Figure 3). The relationships between SOC concentration and terrain attributes were studied for only the sub-watersheds that were completely within the field. There were 23 soil samples located in these sub-watersheds and they were used to create the relationship between SOC concentration and terrain attributes using the DEM with 2 m grid size. SOC concentration was negatively related to slope gradient and topographic characterization index, and positively related to flow accumulation, upstream flow length, and topographic wetness index (Table 2). SOC concentration still had the highest correlation coefficient with topographic wetness index, with a value of 0.80. Compared with the correlation coefficients using all soil samples (Table 1), the correlations among SOC concentration and terrain attributes had a similar distribution but with stronger (positive and negative) relationships. The correlation coefficients between SOC concentration and other terrain attributes, including elevation, plan curvature, profile curvature, total curvature, and stream power index, still had the same sign as Table 1 but they were not significant at $P < 0.05$ level. This suggested that these terrain attributes might not be good predictors for mapping SOC concentration when the area of complete sub-watersheds was used.

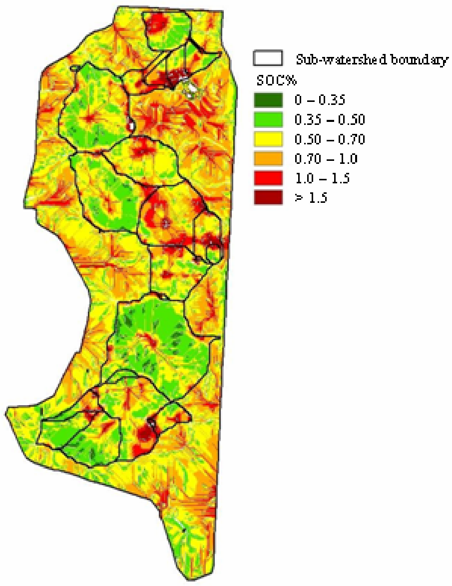

Figure 3. Map of SOC concentration for the field. The black lines within the field were the boundary lines of sub-watersheds

The best regression equation for predicting SOC concentration using the DEM with 2 m grid size included terrain attributes of slope gradient, and topographic wetness index. The equation was listed as follows:

$$\text{SOC \%} = -0.34 + 0.42 / \text{sqrt}(S) + 0.117\ \text{TWI} \quad (3)$$

The R^2 and RMSE values for this model increased to 0.82 and 0.24, respectively. The map of SOC concentration for the covered was developed with the prediction equation. From the sampling, 24 samples were located in the area covered by the complete sub-watersheds. The validation using these 24 samples conducted by linear regression analysis between measured and predicted surface SOC concentrations gave r^2 and RMSE values of 0.59 and 0.273, respectively. The linear regression equation was expressed as follows:

$$\text{SOC}_{\text{Measured}} = 0.887\ \text{SOC}_{\text{Predicted}} \quad (4)$$

Compared with the model that was constructed using all sub-watersheds, both the prediction model and the validation were greatly improved.

The final map of SOC concentration was developed for the DEM with a 2 m grid size. The map was a combination of the two models, using the prediction equation (3) for the area covered by complete sub-watersheds and the prediction equation (1) for the rest of the area (covered by incomplete sub-watersheds) to compute the SOC concentrations (Figure 3).

Table 2. Pearson correlations between SOC concentrations and terrain attributes at the samples locations only located in complete sub-watershed areas

	SOC	Z	S	Fa	Ful	Kpl	Kpr	K	TWI	SPI
Z	ns									
S	-0.58	ns								
Fa	0.42	ns	ns							
Ful	0.62	-0.61	ns	0.78						
Kpl	ns	0.43	ns	-0.83	-0.81					
Kpr	ns	-0.44	ns	0.73	0.68	-0.74				
K	ns	0.47	ns	-0.84	-0.80	0.94	-0.92			
TWI	0.80	-0.52	-0.48	0.65	0.89	-0.72	0.63	-0.73		
SPI	ns	-0.62	ns	0.68	0.87	-0.82	0.73	-0.83	0.72	
TCI	-0.42	ns	ns	-0.99	-0.83	0.90	-0.80	0.91	-0.70	-0.76

ns: Not significant at $P < 0.05$

3.3. Uncertainty analysis with different grid sizes

Three factors, including grid sizes, delineation of sub-watersheds, and sampling locations, were discussed for their effects on prediction of SOC concentrations. The best prediction model for mapping SOC concentration was obtained when grid size was 2 m. This was true in both cases with and without corrupting sub-watershed around the field. In this study, we found that the prediction equation yielded the highest R^2 and the smallest RMSE values when the DEM with 2 m grid size was used. The DEM with 1 m grid size might show too much detail which did not actually reflect the reality of the true topography and caused relatively low R^2 and high RMSE values, where as the DEMs with 4 and 8 m grid sizes might suppress or average the true detail, resulting in poorer prediction models.

The effect of sub-watersheds cut off by the field boundary was also great. Without delineation of complete sub-watershed, the R^2 values with different grid sizes were from 0.48 to 0.58. These values were comparable to other studies conducted by Thompson et al. (2006) in two Kentucky fields (R^2 = 0.43 and 0.47 respectively) and by Terra et al. (2004) in one Alabama field (R2 = 0.52 ~ 0.58 for three grid sizes). We also found that without delineation of complete sub-watersheds the changes of both R^2 and RMSE values were relatively small with different grid sizes. This may indicate that for some data, the change of grid sizes at a certain range might not be a factor affecting SOC prediction.

When only considering the areas covered by the sub-watersheds completely within the field, prediction of SOC concentration from terrain attributes was greatly improved (Equation 2). The R^2 values for the best prediction models for the DEMs with various grid sizes were increased 41% with 2 m grid size. The best model was observed when grid size was 2 m with R^2 value of 0.82 and RMSE value of 0.24.

The locations of soil sampling could also affect the prediction of SOC concentration. The study showed that at least one of the secondary terrain attributes including topographic wetness index, stream power index, and terrain characterization index was used in the best prediction models. Because of the nature of logarithmic functions, these indexes could be irrational when the value of either slope gradient and/or specific catchment area was/were zero. Therefore, when soils were sampled at the location where the calculated values (not necessary to be the actual situation) of slope gradient or/and specific catchment area were zero, these samples would not be able to be used in model development. A soil sample might have been taken at such a location if it was located at a local lowest point or close to a sub-watershed boundary. The number of soil samples taken at locations with zero value of either slope gradient or specific catchment area was shown in Table 3. DEMs with different grid sizes could affect the calculated values of slope gradient and specific catchment area. With 1 m and 4 m grid sizes, the number of soil samples at locations with zero slope gradient and specific catchment area were 10 and 7 samples, and 5 and 2 samples within the areas covered by complete sub-watersheds, respectively. The number was greatly reduced when the grid sizes were 2 and 8 meters. Relatively better SOC prediction models with grid sizes of 2 and 8 meters were also found, indicating that this result may partially be affected by the sample locations. In order to avoid soil samples hitting the zero values of slope gradient and specific catchment area, one way was to avoid taking soil samples at locations close to local lowest point or local highest point or line. The problem of this process was that there were possibilities of missing the sampling locations with high and low SOC concentrations and therefore affecting the prediction of SOC concentration. Another process we might want to consider was to modify the representations of TWI, SPI, and TCI for these extreme cases. Therefore, the irrational logarithmic function could be avoided. Research needed in the future.

4. Summary and Conclusions

In this study, the relationship between SOC concentration and terrain attributes was examined for a crop field located in the coastal plain region of Georgia. The DEM models were created with different grid sizes based on the high accuracy GPS measurement for the field, and terrain attributes were then derived from the DEMs. Sub-watersheds within the field were delineated from the DEMs to improve the prediction of SOC concentration. The study showed that SOC concentrations at a field scale may be improved with delineation of sub-watersheds by using the areas only covered by complete sub-watersheds. A map of SOC concentration for the field could be developed with examining the soil-landscape relations, and could be further refined with delineation of sub-watersheds of the field.

Different grid sizes could affect the prediction of SOC concentration. In this study, the best prediction model was obtained when the DEM with 2 m grid size was used. However, this conclusion may need to be examined further for fields with different sized sub-watersheds. Because of the nature of logarithmic function, the selection of soil sampling locations also needs to be considered to avoid locations close to local lowest point or sub-watershed boundary if TWI, SPI, and TCI were included in the SOC prediction. However, the better way may be to modify the representations of TWI, SPI, and TCI so the limitation of logarithmic function could be avoided. Further studies are needed for the modification.

Table 3. Soil samples located on grid values with 0 value of slope gradient and flow accumulation

Grid size	All soil samples		Soil samples only in complete sub-watershed	
	Total	S=0 or Asc=0 *	Total	S=0 or Asc=0
1 m	45	10	20	5
2 m	45	2	23	1
4 m	45	7	24	2
8 m	45	0	21	0

* S = slope gradient, Asc = specific catchment area

5. References

[1] Chen, F., D. E. Kissel, L.T. West, and W. Adkins. Field-scale mapping of surface soil organic carbon using remotely sensed imagery. Soil Sci. Soc. Am. J. 2000, **64**: 746-753.

[2] Chen, F., D. E. Kissel, L.T. West, D. Rickman, J.C. Luvall, and W. Adkins. Mapping soil organic carbon concentration for multiple fields with image similarity analysis. Soil Sci. Soc. Am. J. 2008, **72**: 186-193.

[3] Dahnke, W.C. and G.V. Johnson. Testing soils for available nitrogen. Soil Testing and Plant Analysis. In R.L. Westerman (ed.) SSSA Book Ser. 1990, **3:** 127-139. Soil Sci. Soc. Am., Madison, WI

[4] Ebinger, M.H., M. Lee Norfleet, D.D. Breshears, D.A. Cremers, M.J. Ferris, P.J. Unkefer, M.S. Lamb, K.L. Goddard, and C.W. Meyer. Extending the applicability of Laser-induced breakdown spectroscopy for total soil carbon measurement. Soil Sic. Soc. Am. J. 2003, **67**: 1616-1619.

[5] Florinsky, I.V., R.G. eilers, G.R. Manning, and L.G. Fuller. Prediction of soil properties by digital terrain modeling. Environmental Modeling & Software. 2002, **17**: 295-311.

[6] Fox, G.A. and R. Metla. Soil property analysis using principal components analysis, soil line, and regression models. Soil Sci. Soc. Am. J. 2005, **69**: 1782-1788.

[7] Fox, G.A. and G.J. Sabbagh.. Estimation of soil organic matter from red and near-infrared remotely sensed data using a soil line euclidean distance technique. Soil Sci. Soc. Am. J. 2002, **66**: 1922-1929.

[8] Gessler, P. E., O.A. Chadwick, f. Chamran, L. Althouse, and K. Holmes.. Modeling soi-landscape and ecosystem properties using Terrain Attributes. Soil Sci. Soc. Am. J. 2000, **64**: 2046-2056.

[9] Hance, R.J. 1988. Adsorption and bioavailability. In R. Grover (ed.) environmental Chemistry of Herbicides (P.1-19). Vol. 1, CRC Press, Boca Raton, FL.

[10] Havlin, J.L., J.D. Beaton, S.L. Tisdale, and W.L. Nelson. 1999. Soil fertility and fertilizers: An Introduction to Nutrient Management. Prentice Hall, Upper Saddle River, NJ.

[11] McCarty, G.W., J.B. Reeves III, V.B. Reeves, R. F. Follett, and J.M. Kimble.. Mid-infrared and near-infrared diffuse reflectance spectroscopy for soil carbon measurement. Soil Sci. Soc. Am. J. 2002, **66**: 640-646.

[12] Moore, I.D., R.B. Grayson, and A.R. Ladson.. Digital terrain modeling: A review of hydrological, geomorphological, and biological applications. Hydrol. Process. 1991, **5**: 3-30.

[13] Mueller, T.G. and F.J. Pierce. Soil carbon maps: Enhancing spatial estimates with simple terrain attributes at multiple scales. Soil Sci. Soc. Am. J. 2003, **67**: 258-267.

[14] Nelson, D.W. and L. E. Sommers. Total carbon, organic carbon, and organic matter. Methods of Soil Analysis: Chemical and Microbiological Properties 1996: 961-1010 Soil Sci. Soc. Am., Madison, WI.

[15] Park, S.J., K. McSweeney, and B. Lowery. Identification of the spatial distribution of soils using a process-based terrain characterization. Geoderma. 2001, **103**: 249-272.

[16] Rodriguez-Murillo, J.C., Organic carbon content under different types of land use and soil in peninsular Spain. Boil fertil Soils, 2001, **33**: 53-61.

[17] Sparling, G.P., D. Wheeler, E.-T. Wesely, and L.A. Schipper. What is soil organic matter worth? J. Envuron. Qual. 2006, **35**: 548-557.

[18] Terra, J.A., J.N. Shaw, D.W. Reeve, E. van Santen, and P.L. Mask. Soil carbon relationships with terrain attributes, electrical conductivity, and a soil survey in a coastal plain landscape. Soil Sci. 169: 819-831.

[19] Thompson, J.A. and R.K. Kolka. Soil carbon storage estimation in a forested watershed using quantitative soil-landscape modeling. Soil Sic. Soc. Am. J. 2005, **69**: 1086-1093.

[20] Thompson, J.A., E.M. Pena_yewtukhiw, and J.H. Grove., Soil-landscape modeling across a physiographic region: Topographic patterns and model transportability. Geoderma. 2006, **133**: 57-70.

[21] Wilson, J.P., and J.C. Gallant. 2000. Digital terrain analysis. In J.P. Wilson and J.C. Gallant (ed.) Terrain analysis. P.1-27. John Wiley & Sons, New York.