The spatial distribution of soil properties and prediction of soil organic carbon in Hayden Prairie and an adjacent agricultural field

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The spatial distribution of soil properties and prediction of soil organic carbon in Hayden Prairie and an adjacent agricultural field

by

Skye Angela Wills

A dissertation submitted to the graduate faculty
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Major: Soil Science (Soil Morphology and Genesis)

Program of Study Committee:
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For the Major Program
"...this picturesque native grassland serves as a measuring stick where the physical characteristics and soil fertility of virgin soil may be compared with the nearby cultivated soil in order to maintain the health of cultivated soils. Citizens of different parts of the state would be wise to preserve virgin prairie so that comparisons with the local cultivated soils might be made with undepleted virgin soils by the soil scientists."

Dr. Ada Hayden
WOI Radio transcript, 1946

Ada Hayden Collection
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# TABLE OF CONTENTS

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>LIST OF FIGURES</td>
<td>vii</td>
</tr>
<tr>
<td>LIST OF TABLES</td>
<td>xi</td>
</tr>
<tr>
<td>ABSTRACT</td>
<td>xiii</td>
</tr>
<tr>
<td>CHAPTER 1. INTRODUCTION</td>
<td>1</td>
</tr>
<tr>
<td>General Introduction</td>
<td>1</td>
</tr>
<tr>
<td>Background</td>
<td>4</td>
</tr>
<tr>
<td>Thesis Organization</td>
<td>13</td>
</tr>
<tr>
<td>References</td>
<td>13</td>
</tr>
<tr>
<td>CHAPTER 2. SPATIAL ANALYSIS OF SOIL PROPERTIES USING SOIL MAP UNITS AND LANDSCAPE POSITIONS</td>
<td>23</td>
</tr>
<tr>
<td>Abstract</td>
<td>23</td>
</tr>
<tr>
<td>Introduction</td>
<td>24</td>
</tr>
<tr>
<td>Materials and Methods</td>
<td>26</td>
</tr>
<tr>
<td>Results and Discussion</td>
<td>30</td>
</tr>
<tr>
<td>Conclusions</td>
<td>40</td>
</tr>
<tr>
<td>References</td>
<td>41</td>
</tr>
<tr>
<td>CHAPTER 3. SPATIAL ANALYSIS OF SOIL PROPERTIES USING GEOSTATISTICS</td>
<td>54</td>
</tr>
<tr>
<td>Abstract</td>
<td>54</td>
</tr>
<tr>
<td>Introduction</td>
<td>55</td>
</tr>
<tr>
<td>Materials and Methods</td>
<td>56</td>
</tr>
<tr>
<td>Results and Discussion</td>
<td>59</td>
</tr>
<tr>
<td>Conclusions</td>
<td>64</td>
</tr>
</tbody>
</table>
CHAPTER 4. EVALUATING GIS AND GEOSTATISTICAL TECHNIQUES FOR DETERMINING THE SPATIAL DISTRIBUTION OF SOIL PROPERTIES

Abstract 74
Introduction 75
Materials and Methods 77
Results and Discussion 83
Summary 87
Conclusions 90
References 90

CHAPTER 5. PREDICTION OF SOIL ORGANIC CARBON CONTENT USING FIELD AND LABORATORY MEASUREMENTS OF SOIL COLOR.

Abstract 107
Introduction 108
Materials and Methods 111
Results and Discussion 114
Conclusions 121
References 123

CHAPTER 6. SOIL ORGANIC CARBON PREDICTIONS USING COLOR, GIS, AND GEOSTATISTICS

Abstract 139
Introduction 140
Materials and Methods 143
Results and Discussion 148
Conclusions 154
References 155
LIST OF FIGURES

CHAPTER 1.

Figure 1. Photographs of Hayden Prairie State Preserve: a & b) 1956 and c & d) 2003. 22

CHAPTER 2

Figure 1. Location of study site on the Iowan Surface in northeastern Iowa, USA. 52

Figure 2. Digital elevation model and slope position with soil series and manually digitized landscape positions. 53

CHAPTER 3

Figure 1. Location of study site on the Iowan Surface in northeastern Iowa. 70

Figure 2. Digital elevation model and slope derived from RTK-GPS data using ArcGIS. 70

Figure 3. Semi-variograms of soil organic carbon content by weight (g kg\(^{-1}\)) and volume (kg m\(^{-3}\)). 71

Figure 4. Ordinary kriging predictions using the semi-variogram models for epipedon thickness, bulk density, and soil organic carbon. 72

Figure 5. Predictions of clay content in surface horizons, epipedons, and subsoils using ordinary kriging. 73

CHAPTER 4

Figure 1. Location of study site on the Iowan Surface in northeastern Iowa, USA. 97

Figure 2. Digital elevation model and slope derived from RTK-GPS data using ArcGIS. 98

Figure 3. Epipedon thickness predicted across the agricultural field and prairie using soil map units, landscape positions, and ordinary kriging. 99
Figure 4. Bulk density of all described cores for surface samples, predicted across the agricultural field and prairie using soil map units, landscape positions, and ordinary kriging.

Figure 5. Epipedon soil organic carbon content by weight, g kg$^{-1}$, content across the agricultural field and prairie using soil map units, landscape positions, and ordinary kriging grid (5m) predictions.

Figure 6. Epipedon soil organic carbon content by volume, g m$^{-3}$, for soil map units, landscape positions, and ordinary kriging grid (5m) predictions.

Figure 7. Distribution of surface horizon clay content soil map unit means, landscape position means and ordinary kriging grid (5m) predictions.

Figure 8. Distribution of surface horizon total sand content (%) across the agricultural field and prairie using soil series means, landscape position means and ordinary kriging grid (5m) predictions.

Figure 9. Distribution of surface horizon clay content (%) across the agriculture field and prairie using soil series means, landscape position means and ordinary kriging predicted.

Figure 10. Distribution of clay content in surface horizons epipedons and subsoils across the agriculture field and prairie using and ordinary kriging grid (5m) predictions.

CHAPTER 5

Figure 1. Location of study site on the Iowan Surface in northeastern Iowa, USA.

Figure 2. Average particle size distribution of analyzed epipedon and subsoil horizons in agricultural field and prairie.

Figure 3. Regression of soil organic carbon content measured by sample, horizon, and depth increment with a) clay content and b) sand.

Figure 4. Soil organic carbon content and prepared sample chroma meter Munsell values for a) SOC (g kg$^{-1}$), b) SOC (kg m$^{-3}$), c) log SOC (g kg$^{-1}$), and d) Log SOC (kg m$^{-3}$).
Figure 5. Actual and predicted soil organic carbon content using a) SOC (g kg\(^{-1}\)) and b) Log SOC (kg m\(^{-3}\)).

Figure 6. Actual and predicted soil organic carbon content by volume (kg m\(^{-3}\)) of: a) agricultural field and b) prairie.

CHAPTER 6

Figure 1. Site location in Howard County, Iowa. Nested grid sampling scheme including all cores analyzed for color and soil organic carbon, and the validation set.

Figure 2. Digital elevation model, percent slope and topographic wetness index derived from RTK-GPS data analyzed with Geostatistical Wizard and TAPES-G extensions of ArcGIS.

Figure 3. Soil organic carbon content (kg m\(^{-2}\) to a depth of 0.2m) predicted by color for the agricultural field (a) and the prairie (b).

Figure 4. Soil organic carbon content (kg m\(^{-2}\) to a depth of 0.2m) predicted by ordinary kriging, topographic wetness index (TWI) and soil series for all cores (training and validation sets).

Figure 5. Ordinary kriging prediction versus measured soil organic carbon content (kg m\(^{-2}\) to a depth of 0.2m) values for validation set cores only.

Figure 6. Soil organic carbon (SOC) content (kg m\(^{-2}\)) predictions to a depth of 0.2m using ordinary kriging of measured SOC and co-kriging with measured SOC and SOC predicted with description colors and chroma meter colors.

Figure 7. Soil organic carbon (SOC) content (kg m\(^{-2}\)) predictions to a depth of 1.0m using ordinary kriging of measured SOC and co-kriging with measured SOC and SOC predicted with description colors and chroma meter colors.

Figure 8. Soil organic carbon content (kg m\(^{-2}\)) predictions to a depth of 0.2m using GIS classes of soil series and landscape positions.

Figure 9. Soil organic carbon content (kg m\(^{-2}\)) predictions to a depth of 1.0m using GIS classes of soil series and landscape positions.
LIST OF TABLES

CHAPTER 2

Table 1. Number of cores taken in each soil map unit and landscape position. 46
Table 2. Epipedon property means for all cores taken by soil map unit in each land use. 47
Table 3. Epipedon property means of laboratory cores for soil series in each land use. 48
Table 4. Particle size distribution for the surface horizons of laboratory analyzed cores in each land use and soil series. 49
Table 5. Epipedon property means for landscape positions in each land use. 50
Table 6. Particle size distribution for the surface horizon of analyzed cores in each land use and landscape position as percent of total mineral matter 51

CHAPTER 3

Table 1. Summary of spherical semi-variogram model parameters and root mean square prediction error of ordinary kriging for epipedon properties. 68
Table 2. Summary of spherical semi-variogram model parameters and root mean square prediction error of ordinary kriging for surface horizon particle size distribution fractions. 69

CHAPTER 4

Table 1. Average epipedon values weighted by area using soil map unit, landscape position, and ordinary kriging. 94
Table 2. Average particle size fractions of laboratory core surface horizons weighted by area using soil series, landscape position, and ordinary kriging. 95
Table 3. Average particle size fractions of selected core epipedon and subsoil horizons weighted by area using soil series, landscape position, and ordinary kriging. 96
CHAPTER 5

Table 1. Soil series and great group classification of cores analyzed for soil organic carbon content and soil color in the agriculture field and the prairie. 128

Table 2. Summary table of abbreviations used for soil organic carbon content and color measurement combinations. 128

Table 3. Summary of epipedon and subsoil properties for agriculture field and prairie. 129

Table 4. Ranges of soil organic carbon content and Munsell soil color measurements taken with chroma meter and Munsell Soil Color Cook for the agriculture field (Ag) and prairie (Pr). 130

Table 5. Summary table of coefficient of determination values for linear regression of SOC. 131

CHAPTER 6

Table 1. Equations derived from regression of training set samples and used to predict soil organic carbon content in all cores. 165

Table 2. Soil organic carbon content models using soil color to predict soil organic carbon and Log(10) soil organic carbon by weight. 166

Table 3. Coefficient of determination and root means square prediction error of model predictions and measured soil organic carbon content of the validation set. 167

Table 4. Range of terrain attributes in the agriculture field (a) and the prairie (b). 168

Table 5. Coefficient of determination and root means square prediction error for model predictions and measured soil organic carbon content of the validation core set. 169

Table 6. Mean soil organic carbon contents of each land use using GIS class averages weighted by area. 170

Table 7. Mean and range of soil organic carbon models predicted on a raster basis. 171
Table 8. Range and mean of measured and predicted soil organic carbon content for all cores and just those used in model validation in the agriculture field. 172

Table 9. Range and mean of measured and predicted soil organic carbon content for all cores and just those used in model validation in the prairie. 173
ABSTRACT

While the effect of cultivation on soil properties has been well documented, its effect on the spatial distribution of soil properties is less well understood. The purpose of this study is to use GIS classes, soil map units and landscape positions, and geostatistics to characterize the spatial distribution of soil properties in a native prairie and agriculture field. A secondary purpose is to use soil color in combination with these techniques and terrain attributes to predict soil organic carbon (SOC) content to 0.2 and 1.0m depths across each land use. Each land use was sampled in an unbalanced hierarchical nested grid for a total of 203 cores. Soil color was measured by Munsell Soil Color Book and chroma meter with three types of samples: a) prepared samples, ground to <2mm, b) horizon peds, and c) split cores (measurements taken at horizon and depth increment mid-points). Standard techniques were used to describe all cores and analyze a subset (63 in each land use) for soil organic carbon (SOC), bulk density, percent water stable aggregates (WSA), pH, and surface horizon particle size distribution. Bulk density, pH, and WSA are not spatially dependent using any technique. Using GIS classes, the prairie has more significant differences in soil properties between classes. Soil series partitioned more properties into significantly different classes than landscape positions did. The spatial dependence of SOC content depends on the method used and scale in question. The agricultural field is more homogenous, but geostatistics show that it has spatial dependence with small-scale continuity. SOC content distribution is related to localized, mid-slope wetness in the prairie that no longer occurs in the agricultural field due to artificial drainage. Only a few models in this study were generally satisfactory
for predicting SOC contents. On individual samples, SOC content was significantly related to soil color, including field measurements by traditional descriptions and chroma meters on intact cores. When these techniques are used to predict SOC on whole cores the relationships are not significant. The best predictors of SOC content are topographic wetness index in the agricultural field and kriging and co-kriging in the prairie. Across each land use, the average land use predictions vary by 2.4 kg m\(^{-2}\) for 0.2m and 3.8 kg m\(^{-2}\) for 1.0m in the agriculture field and 6.2 kg m\(^{-2}\) for 0.2m and 19.0 kg m\(^{-2}\) for 1.0m in the prairie. These differences are significant and the model chosen will impact research conclusions or management decisions made from SOC predictions. In conclusion, agricultural cultivation has changed the distribution of SOC across the landscape and thus different models are needed to make accurate predictions.
CHAPTER 1. INTRODUCTION

The impact of human land use on soils is profound. These impacts are apparent on regional and local scales. In Iowa, more than 90% of the land has been extensively cultivated, drained, fertilized and/or converted to vegetation much different than would naturally exist (Whitney, 1994; Thompson, 1992). Soil researchers have long recognized the impact of cultivation on soil properties. Jenny (1941) stressed the importance of human impact on the five state factors of soil formation: climate, organisms, topography, parent material and time. Subsequent authors have proposed ways to express human impacts on soil through qualitative methods (Sandor, et al., 2005; Amundson and Jenny, 1991; Yaalon and Yaron, 1966; Bidwell and Hole, 1964). More quantitatively, numerous studies have outlined the changes cultivation causes in individual soil properties. Cultivation influences epipedon thickness because of differences in bioturbation, compaction, erosion, or deposition (Buol et al., 2003; Hole, 1981). Cultivation has been shown to increase bulk density (e.g. Cihacek and Ulmer, 1986; Coote and Ramsey, 1983); decrease soil carbon content (e.g. Fenton et al., 1999) and disrupt soil structure (e.g. Kay, 1995; Perfect et al., 1990) through mechanical action and decreasing root and microbial biomass (Stahl et al., 1999; Harris et al., 1996; Kay, 1995).

Despite this robust historical data set, the effect of cultivation on the spatial distribution of soil properties is much less well understood. While the literature is replete with examples of land use comparisons, there are fewer that systematically examine any differences in the distribution of those properties. Cultivation has been shown to decrease the variability of soil organic carbon, SOC, (Cattle, 1994) and increase the maximum
distance of spatial dependence for SOC and other properties (Cambardella et al., 1994; Robertson et al., 1993). Paz-González et al. (2000) found that cultivated soils were more homogeneous than soils under natural vegetation, with increased small scale continuity (reduced nugget effects) of organic matter and cation exchange capacity. Addressing the uncertainty in spatial predictions has grown in importance as minimally disturbed soils become increasingly rare. Pedological insights into human impacts are crucial to developing environmentally benign yet economically sustainable soil management practices (Lal and Stewart, 1995).

The primary focus of this study is to determine the influence of land use on the distribution of soil properties under an agricultural field and native prairie, on the Iowan Surface in northeast Iowa. Two questions are evaluated:

1) What are the spatial distributions of soil properties?

2) Has agricultural land use changed these distributions?

I attempt to answer these questions using two types of models: GIS and Geostatistics. For GIS, I used previously delineated soil series map unit boundaries (Iowa Cooperative Soil Survey, 2003) along with my own data collection. For an alternate GIS landscape characterization, I used Ruhe’s (1975) landscape position model to classify soil core locations by landscape position (summit, shoulder, backslope, and footslope). I created digital maps of soil series map units and landscape position in order to predict and evaluate the distribution of soil properties across each land use.

Geostatistical analyses were done by fitting semi-variogram models to the soil property autocorrelation (variance with distance). The parameters of these models were used to evaluate and compare the spatial dependence of each property in the prairie and the field.
Finally, predictions using GIS and geostatistics were compared by indicated spatial dependence, prediction accuracy, and land use averages.

There is particular interest in quantifying the distribution of soil organic carbon (SOC) across land uses because of its importance in biogeochemical cycles and soil and environmental quality. Soils can "sequester" or act as carbon sinks (e.g. Lal, 2002, Hanson et al., 2001). To promote carbon sequestration through policy and management, predictive mapping of SOC content is necessary to understand carbon changes across landscapes (Bell et al., 2000). Soil carbon has been shown to be spatially dependent, varying laterally both by and within soil type and landscape position (Young and Hammer, 2000a,b; Walker et al., 1996). Soil carbon is also stratified vertically within a given solum. SOC content is greatest near the surface where biological inputs are greatest (Stevenson, 1994; Jenny, 1980). Therefore, the methods in which data are collected and aggregated can influence or even determine estimates of field and regional scale carbon cycles. To calculate total carbon changes on a field or regional scale, more efficient sampling and measurement schemes are needed to more accurately predict soil carbon.

A secondary focus of this study is to evaluate the use of various models for quantifying SOC. The key questions asked include:

1) How is the estimation of SOC distributions over each land use affected by the technique used: GIS delineation and geostatistical analysis?

2) Do average SOC estimates change when different modeling techniques are used?

3) Can soil color be used as an SOC proxy, and will its use in geostatistical analyses improve prediction performance and efficiency?
I used GIS classes from digital soil series and landscape position maps, derived terrain attributes, and geostatistical techniques to predict SOC content across both land uses. Soil color measurements, obtained through various techniques, were used to predict SOC content of individual samples. The best relationships between SOC and soil color were used to improve each of the GIS, terrain attribute, and geostatistical prediction strategies. Finally, I compare the predicted values and errors from each land use and technique.

Background

Study Area

The study areas are the Hayden Prairie State Preserve and an adjacent agricultural field in northeast Iowa. It is estimated that prairie once covered 28.6 million of Iowa’s 35.8 million acres (Iowa Department of Natural Resources, 2000). Today less than 0.01% remains. Of those remnants, more than half may be of poor quality. Hayden Prairie is a 240 acre state preserve located in northern Howard County, Iowa. It is the largest remnant prairie in Iowa outside of the Loess Hills.

Most of the soils in this area are formed in one to two meters of Iowan Surface pedisediment, which overlies a thick, dense Pre-Illinoian glacial till (Prior, 1991; Buckner, 1974; Ruhe, 1969). Tallgrass prairie was the native vegetation for the past 8,000 to 9,000 years (Thompson, 1992). Soils formed from this combination of the Iowan Surface deposits and tallgrass prairie are extensive in Iowa and southeastern Minnesota, with more than 80% of the area currently dedicated to row crop production (Iowa Department of Natural Resources, 2000). Hayden Prairie is perhaps the only remaining large prairie remnant on the Iowa Surface, while the cropped field represents the area’s predominant land use. The
preserved native prairie and cultivated agricultural field provide an ideal contrast to evaluate the effects of a century’s worth of agricultural cultivation on soil property distribution.

**Classifying and Mapping Soil Properties**

**Soil Map Unit Delineations**

Soil maps are a means of conveying information about soil properties. Soil map units represent soil classes, defined by a collection of soil properties, gathered into geographic units (Buol et al., 2003; Arnold and Wilding, 1991). Soils can be mapped for a particular trait or combinations of traits. Ideally, map units should be composed of a consistent mix of soils and soil properties (Hole and Campbell, 1985). Every soil map represents information that is simplified and organized based on the mapmaker’s underlying understanding of soil and its distribution across the landscape. In the United States, soil map units are grouped based on the underlying principles of Soil Taxonomy (Soil Survey Staff, 1999).

Maps are abstract models of spatial phenomena. Soil map units appear on a map as discrete, homogeneous two-dimensional bodies. This implies that properties are constant within a given map unit and change abruptly at its boundaries. This does not reflect reality. Soil properties are generally considered to be continuous across a landscape (Wagenet et al., 1991). Often, all properties do not change simultaneously and sharply at a boundary line; they can change gradually and at different rates from one map unit to the next. Within map units, there is a varying degree of heterogeneity, or inclusion of unlike soils (Hole and Cambell, 1985; Wilding and Drees, 1983). Map unit heterogeneity can lead to difficulties in using the map to predict properties at any point within or along the boundary of a soil map unit. Despite these problems, soil maps provide a readily available source of soil property
information across a landscape. These maps can be used to predict and model properties that were not explicitly classified in the map itself. For instance, Burke et al., (1989) quantified soil carbon across the United States using digitized soil maps. In Iowa, Paustian et al. (2002) used parameters from digital soil maps in carbon model simulations.

Landscape Positions

Topographic information can also be used to map and predict the distribution of soil properties. Landscape topography is closely linked to soil properties and variability. Landforms and soils are closely related because the same factors influence their properties and evolution. Slopes reflect the climate, lithology, time, and processes that created them (Ritter et al., 1995). Soils develop through interactions of time, topography, biota, parent material, and climate (Jenny, 1941). Landscapes, both forming and being formed by soils, are a natural scale for studying soil properties.

Earth scientists divide landscapes into elements, or landscape positions, that can be studied and compared (Ventura and Irvin, 2000; Brubaker et al., 1993; Daniels and Hammer, 1992; Bloom, 1991; Conacher and Dalyrmples, 1977; Ruhe, 1975;). Landscape positions offer a potentially easy to manage unit (in that they are geographically continuous) that can be identified in the field (Brubaker et al., 1994). Soil properties often vary in a systematic manner across landscape positions. Texture and soil thickness have been found to change progressively across the landscape with distance from the summit (Burra and Scholtes, 1986; Malo et al., 1974; Kleiss, 1970; Walker, 1966). Information about landscape positions can be applied to similar areas without extensive soil tests. Soil properties can also be related and predicted by landscape position (Young and Hammer, 2000; Brubaker et al., 1994; Aguilar et al., 1988;). Jones et al. (1989) found that soil productivity could be related
to soil properties characteristic to each landscape position. Landscape positions are usually visually identified in the field. While this may be practical for on-site field managers, it does not allow remote extrapolation of properties to a wider area. There are no widely available maps, as there are for soils, which can be used to convey landscape position properties across the landscape.

Landscape positions are not always discrete and their identification in the field is subjective (Gerrard, 1981). To counter these problems, researchers are developing objective methods of defining and using landscape positions continuously across the landscape. Pennock et al., (1994) used statistically selected landform-soil complexes to improve the assessment of human activity on soil properties. Relative elevation and slope shape can serve as a proxy for landscape position designation. Digital elevation models can be used to derive landform attributes that can be used to predict soil properties (Moore et al., 1991; Odeh et al., 1994). Gessler et al. (2000) used digital elevation models along with hydrologic parameters to select pedons for sampling and prediction of soil carbon. Ventura and Irvin (2000) used automated fuzzy set algorithms to classify areas into landscape positions based on properties including slope, curvature, and elevation. As techniques for elucidating landscape position improve, describing soil properties with them will become more useful.

**Geostatistics**

Geostatistics are a branch of statistics dealing with spatial phenomena in the earth sciences. Although geostatistics were initially developed to describe the spatial variability in ore deposits, they can be used to analyze any feature that exhibits spatial dependence (Webster and Oliver, 2001; Journel and Huijbregts, 1978; Matheron, 1963). Geostatistics rest on the principle that things that are closer together are more alike than things that are
farther apart. This central theme of geostatistics is known as the regionalized variable theory and the complementary function is known as a semi-variogram (Burgess and Webster, 1980a). The regionalized variable theory allows us to consider the spatial variability of a soil property as a stochastic model. Kriging uses the semi-variogram to predict values at unobserved locations using minimization of errors (Krige, 1966). These principles have been applied to soil science for over two decades (e.g. Burgess and Webster, 1980a,b; Webster and Burgess, 1980). New computer applications have allowed more wide-spread development and use of geostatistical techniques. However, there are still many applications of geostatistics that have not yet been explored.

Semi-variogram

The semi-variogram is a function that describes the relationship between attribute values and distance. The semi-variogram ($\gamma$) is equal to half the expected squared difference between values of an attribute ($z$) at point $i$ and another point $h$ distance away ($i + h$) (Burgess and Webster, 1980a). The distance between points ($h$) is known as the lag.

$$\gamma(h) = \frac{1}{2} \mathbb{E} [ \{z(i) - z(i + h)\}^2 ]$$

The value of the empirical or sample variogram can then be estimated for all pairs of points $h$ distance apart with $(n-h)$ being the number of points at lag $h$. (Webster and Oliver, 2001; Goovaerts, 1999):

$$\hat{\gamma}(h) = \frac{1}{2(n-h)} \sum_{i=1}^{n-h} \{z(i) - z(i + h)\}^2$$
In order to calculate statistics for a set \((n-h)\), there must be repeated observations the same distance apart. To obtain repeated values, lag classes are created for a range of distances, or tolerance regions (Cressie, 1993). Each lag class will contribute only one estimate to the semi-variogram. Arbitrary but constant increments are often used to designate lag classes, though the smoothness of the variogram will depend on the increment chosen (Webster and Oliver, 2001; Myers, 1997). Distance and direction lag classes can also be defined to evaluate anisotropy (Myers, 1997; Cressie, 1993).

Most semi-variograms useful to soil scientists have three main features that describe the spatial distribution of the attribute in question (Webster and Oliver, 2001). The nugget is the value of the semi-variogram as distance \((h)\) approaches zero. The nugget effect is due to error in measurement, spatial variation that occurs within the sampling distance interval, and random events. The range is the distance over which spatial dependence is exhibited or where the semi-variogram reaches its maximum level. The sill is the value of the semi-variogram beyond the range or past the distance where spatial dependence is exhibited. Although these features of a sample semi-variogram can be used to compare and understand different spatial situations, they are of limited analytical value. To use the semi-variogram for prediction a functional model must be created and observed.

In order to use a semi-variogram for prediction, a theoretical variogram model must be fit to the sample variogram. Spherical and exponential variograms are two commonly used to model soil properties. There are many books outlining common theoretical variogram models including Cressie (1993) and Webster and Oliver (2001). Models may be fit for best visual fit, but statistically based procedures such as least squares fitting are preferred (Webster and Oliver, 2001; Cressie, 1993). Once the semi-variogram has been fit
its function can be used to krig. Kriging is a general term for a variety of generalized least squares estimation algorithms (Goovaerts, 1999; Journel, 1985). It is a method of weighted averaging of observed values of a property within neighborhoods (Webster and Oliver, 2001). Predicted values can then be interpolated or connected by isarithm lines to create a map over the area of interest.

**Soil Organic Carbon**

Soil organic carbon (SOC) is of interest for many reasons. SOC content is often indicative of soil health and management sustainability. In a review of SOC management, Reeves (1997) found that SOC content was the most commonly chosen indicator of soil quality. Soil organic matter, which contains SOC, has been shown to play a key role in soil tilth and productivity (Tisdall and Oades, 1982; Ulery et al., 1995). It can influence soil warming rates, water retention, and nutrient exchange (Buol et al, 2003; Stevenson, 1994). SOC also has an important role in biogeochemical cycles and environmental quality. The amount and types of SOC affect bioactivity and bioavailability of heavy metals and organic pesticides (Stevenson and Cole, 1999; Pierzynski et al., 1994; Stevenson, 1994). SOC is considered an important pool for carbon storage and exchange with atmospheric carbon dioxide as well. The Kyoto Protocol (Article3.3) recognizes terrestrial pools for their potential to sequester carbon and earn carbon credits (Bruce et al., 1999).

SOC content is influenced by many factors including native vegetation, land use, management practices, other soil properties, and topography (Follett, 2001; Bell et al., 2000; Franzlubber et al., 2000; Franzmeier et al., 1985; Jenny, 1980). SOC exchanges with atmospheric carbon pools in response to changes in crop inputs, residue decomposition, erosion, and soil aggregate breakdown (Bruce et al., 1999; Stevenson and Cole, 1999). The
numerous interactions between these factors create a complex gradient of SOC content over a landscape (Bird et al., 2001). Realizing the potential of carbon sequestration in soils depends on strengthening spatial databases of soil carbon pools under different land uses and management practices (Lal et al., 2001; Kern, 1994).

Soil Organic Carbon and Soil Color

As the measurement of SOC becomes more important due to environmental concerns, better methods are needed to assess it. Direct measurement of SOC can be expensive and time-consuming. It is complicated by the need for many samples to assess spatial heterogeneity (Bird et al., 1999). Soil color can serve as a cost effective proxy for determining organic-matter (which includes SOC) content (Konen, 2003; Schulze et al., 1993; Fernandez, 1988). Soil color is one of the most obvious features of soil morphology and organic matter has long been known as one of the primary pigmenting agents in soil (Buol et al., 2003; Simonson, 1993; Robinson and McCaughey, 1911).

The Munsell Color System is used for soil field descriptions in the United States (Schoenberger, 1993). Soil samples have traditionally been visually matched to a color chip with a given hue, value, and chroma. Although soil color chips are standardized, there is still a certain amount of subjectivity and variability in their use due to the influence of an individual human eye (Post et al., 1993). Fortunately, there are now affordable and rapid instruments that can quantify soil color reliably and accurately (Torrent and Barron, 1993). Konen (2003) used such an instrument to develop satisfactory regressions between soil organic matter and color components on topsoil samples on the Des Moines Lobe, Iowa. Working in Indiana, Schulze et al. (1993) found that relationships between color and soil organic matter were similar for landscapes with same parent material and texture but not for
those that differed significantly in those parameters. Fernandez et al., (1988) found that color and organic matter were strongly correlated when calibrations were done on a field by field basis. The ISU Pedometrics group (Burras et al., 2005) is attempting to create equations for both field and laboratory color measurements in various parent materials and land uses of Southern Iowa.

Land Use Impacts on Soil Organic Carbon Content and Variability

Land use affects SOC content by changing the balance of inputs and removals of organic matter. SOC content gains in terrestrial ecosystems are influenced by photosynthesis inputs from plants (Bruce et al., 1999). SOC can be lost by increasing rates of decomposition or increasing losses to erosion (Bruce et al., 1999; Stevenson and Cole, 1999). Franzlubbers (2000) found that vegetation type and management had a significant impact on SOC. The greatest reductions and redistributions of SOC contents occur due to cultivation.

Cultivation can cause losses of 20 to 40% SOC (Davidson and Ackerman, 1993) primarily through changes to land cover and tillage (Gerrard, 1981; Troeh, 1999). Cultivation decreases SOC largely by three mechanisms. First, plant residue is removed at harvest reducing the carbon inputs into the soil. Second, tillage causes aggregate breakdown and exposure of previously protected organic matter (Elliot, 1986) leading to increased rates of decomposition and CO2 release after cultivation (Reicosky, 2002). Third, because SOC is concentrated near the soil surface, erosion of topsoil results in losses of SOC (Lal et al., 2001).

Soil texture, structure, mineralogy, and organic matter properties influence soil erodibility (i.e, the “K” factor of the USLE) (Troeh et al., 1999). Cultivation has been shown to cause changes in soil structure, aggregate stability, organic matter, and carbon content
within decades (Fenton et al., 1999; Konen, 1999; Stahl et al., 1999; Richter, 1990; Zhang et al., 1988; Mann, 1986; Gidden, 1957; Anderson, 1949). Most crop vegetation does not provide adequate cover to protect soil from the erosive action of rainfall and surface flow (Gerrard, 1981; Troeh et al., 1999). When vegetative cover is removed, the potential for water erosion increases by a power function proportional to slope length and steepness. Thus, cultivation can increase sediment yields from hillslopes by one or two orders of magnitude relative to an uncultivated field (Carson and Kirkby, 1972, Osterkamp and Toy, 1997; Ruhe, 1969; Saunders and Young, 1983; Toy, 1982). This erosion can result in as much as 70% of eroded SOC being redistributed across the landscape (Follet et al., 2001). While it is evident that post-European settlement cultivation has caused increases in soil erosion and therefore losses and changes in the distribution of SOC, it is unclear what the scale of those changes are.

**Dissertation Organization**

This dissertation format includes a general introduction (Chapter 1), 5 independent technical papers (Chapters 2 through 6), and a general summary and conclusion (Chapter 7). Chapters 2, 3, and 4 focus on evaluating the distribution of soil properties across and between the agriculture field and the prairie with GIS classes (Chapter 2), geostatistics (Chapter 3), and a summary and comparison of the two techniques (Chapter 3). Chapter 4 reports the use of soil color, measured through various techniques, to predict SOC on individual samples. Chapter 5 uses the techniques established in Chapters 2-5 to predict SOC content across each land use.
References


Figure 1. Photographs of Hayden Prairie State Preserve: a & b) 1956 (Hayden Prairie Images, Iowa State University Library, Special Collections Department) and c & d) 2003.
CHAPTER 2. SPATIAL ANALYSIS OF SOIL PROPERTIES USING SOIL SERIES AND LANDSCAPE POSITIONS

A paper to be submitted to Soil Science Society of America Journal

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Abstract

A central concept of pedology is that landforms and soils occur in repeating and predictable patterns. The purpose of this study is to evaluate the use of soil series map units and landscape positions for explaining the spatial distribution and variability of soil properties in a native prairie and agricultural field. Cores were taken on Hayden Prairie State Preserve and a contiguous adjacent agricultural field on a nested grid, 203 cores in each land use. All cores were described with standard nomenclature, and a subset was analyzed for soil organic carbon (SOC), water stable aggregate content, pH, and surface horizon particle size distribution. Analysis of variance was used both to compare means of soil series map units and landscape position classes both within and between land uses. Soil series partitioned more properties into significantly different classes than landscape positions did. Soil series were significantly different within both land uses for epipedon thickness, elevation, and slope. Landscape positions were only significantly different for epipedon thickness and elevation in the agricultural field and prairie. In the prairie, soil series had significantly different particle size and SOC contents and landscape positions had significantly different pH. Analysis of variance on individual classes between land uses was also used to examine the effect of land uses on soil properties. Prairie classes consistently have significantly greater epipedon thickness and percent WSA content with lower epipedon bulk density.
Introduction

A central concept of pedology is that landforms and soils are associated in repeating and predictable patterns (Daniels and Hammer, 1992, Ruhe, 1975: Milne, 1935). While the relationship between landform and soils is complex and sometimes difficult to interpret, it allows soil scientists to separate soils into classes across the landscape. Two traditional methods of conveying these patterns are through soil series maps and landscape positions. Soil map units represent soil classes, defined by collection of soil properties, gathered into geographic units (Buol et al., 2003; Arnold and Wilding, 1991). Landscape positions are defined by models that separate the landscape by surface characteristics. Standard models exist so that individual landscape positions can be studied and compared (Ventura and Irvin, 2000; Daniels and Hammer, 1992; Bloom, 1991; Conacher and Dalyrmple, 1977; Ruhe, 1975). The purpose of this study is to evaluate the use of soil series and landscape position map units for explaining the variability and spatial distribution of soil properties in a native prairie and agricultural field.

Soil maps convey information about the soil to land users. In the United States, soil map units are grouped based on the underlying principles of Soil Taxonomy (Soil Survey Staff, 1999). Known information about a map unit can be used to extrapolate those properties to similar map units across landscapes and regions (Bouma et al., 1999; Burke et al., 1989; Voltz and Webster, 1990). There are some difficulties in doing this. Soil map units appear on a map as discrete, homogeneous two-dimensional bodies. This implies that properties are constant within a given map unit and change abruptly at its boundaries. This does not reflect reality for most soils. Soil properties are generally considered to be continuous across a landscape (Wagenet et al., 1991). Most properties do not change
simultaneously at a boundary line; they change gradually from one map unit to the next. Within map units, there is a varying degree of heterogeneity, or inclusion of unlike soils (Hole and Cambell, 1985; Wilding and Drees, 1983). Map unit heterogeneity can lead to difficulties in using the map to predict properties at any point within or along the boundary of a soil map unit. Despite these problems, soil maps provide a readily available source of soil property information across a landscape. These maps can be used to predict and model properties that were not explicitly classified in the map itself. For instance, Burke et al., (1989) quantified soil carbon across the United States using digitized soil maps. In Iowa, Paustian et al. (2002) used parameters from digital soil maps in carbon model simulations.

In this study, we use previously delineated soil series map unit boundaries (Iowa Cooperative Soil Survey, 2003) along with our own data collection to evaluate soil series map units. We will use them to predict soil properties and evaluate their usefulness in determining the spatiality of each land use.

Landforms and soils are closely related because the same factors influence their properties and evolution. Slopes reflect the climate, lithology, time, and processes that created them (Ritter et al., 1995). Soils develop through interactions of time, topography, biota, parent material, and climate (Jenny, 1941). Landscape positions, both forming and being formed by soils, are a natural scale for studying soil properties.

Soil properties are known to vary with the landscape in a repeating and predictable way (Daniels and Hammer, 1992; Ruhe, 1975; Simonson, 1959). Texture and soil thickness have been found to change progressively across the landscape with distance from the summit (Burras and Scholtes, 1986; Malo at al., 1974; Kleiss, 1970; Walker, 1966). Information about landscape positions can be applied to similar areas without extensive soil tests. Soil
properties can also be related and predicted by landscape position (Young and Hammer, 2000a & b; Brubaker et al., 1994; Aguilar et al., 1988). Jones et al. (1989) found that soil productivity could be related to soil properties characteristic to each landscape position.

Landscape positions offer a potentially easy to manage unit (geographically continuous) that can be identified in the field (Brubaker et al., 1994). However, landscape positions are not always discrete and their identification is often subjective (Gerrard, 1981).

Landscape positions are usually visually identified in the field. While this may be practical for on-site field managers, it does not allow remote extrapolation of properties to a wider area. There are no widely available maps, as there are for soil series, which can be used to convey landscape position properties across the landscape. In this study, we use Ruhe's (1975) landscape position model to classify soil core locations by landscape position (summit, shoulder, backslope, and footslope). We also created digital maps of landscape position in order to predict and evaluate the distribution of soil properties across each land use. Finally, these predicted distributions were compared to those predicted with soil series.

**Materials and Methods**

**Study Area**

The study sites are on the Hayden Prairie State Preserve and an adjacent agricultural field in northeast Iowa (Figure 1). Most of the soils in this area are formed in one to two meters of Iowan Surface pedisediment, which overlies a thick, dense Pre-Illinoian glacial till (Ruhe, 1969; Prior, 1991). Tallgrass prairie was the native vegetation for the past 8,000 to 9,000 years (Thompson, 1992). Soils formed from this combination of the Iowan Surface deposits and tallgrass prairie are extensive in Iowa and southeastern Minnesota, with more
than 80% of the area currently dedicated to row crop production (Iowa Department of Natural Resources, 2000). Hayden Prairie is perhaps the only remaining large prairie remnant on the Iowa Surface while the cropped field represents the area’s predominant land use. The prairie and field provide an ideal contrast to evaluate the effects of a century worth of agricultural cultivation on soil property distribution.

**Sampling**

Each land use was sampled in an unbalanced hierarchical nested grid. This was done to determine the scale of spatial dependence and improve sampling efficiency (Borgelt et al., 1997; Oliver and Webster, 1986). A square grid was created and georeferenced to minimize the number of samples while assuring a range of spatial scales. A 24 ha area of both the prairie and agricultural field was divided into a 100m grid. This grid was separated into 6 blocks. Within each block, one 100m square was randomly selected for further division into a nested grid. Each nested grid was composed of grid points that were 50, 25, 12.5, 5 and 2.5m a part (Figure 1). Cores (0.05m x 1.5m) were taken at each grid node with a truck mounted Giddings hydraulic soil probe. A total of 203 cores were taken in each land use. Sixty-three of those cores were analyzed for soil organic carbon (SOC) content, pH and water stable aggregate content (WSA).

**Field Description**

All 406 sampled cores were described and analyzed for bulk density. Field descriptions were done using standard techniques and nomenclature (Schoenberger et al., 2002). Bulk density was determined on horizons and samples taken from predetermined depth increments of 0-5, 5-10, 15-30, 30-50, and 50-100cm for each core. A portion of each
horizon and depth increment was cut, weighed, and oven dried to determine bulk density by a modified volumetric core method (Konen, 1999; Soil Survey Staff, 1996).

**Laboratory Analysis**

Laboratory analyses were done on the samples from 100m grid cores and one randomly selected nested grid from each land use (63 cores from each land use). These cores will be referred to from this point on as laboratory cores. The analyses included pH, soil organic carbon, chroma meter color, water stable aggregate content, and surface horizon texture (Soil Survey Staff, 1996). A subset of these cores chosen to represent all landscape positions were also analyzed for particle size distribution of all horizons. Samples were divided by horizon and depth increment for each core analyzed. Samples were ground to pass a 2mm sieve for further analysis. Chroma Meter color was used to determine Munsell hue, value and chroma for moist and dry ground samples (Konen et al., 2003). Percent water stable aggregate (WSA) content was determined on samples of depth increments 0-5, 5-10 and 15 cm to the bottom of the epipedon. Aggregates having 0.5 - 1 mm diameters were wet sieved as outlined by the Soil Survey Staff (1996). The average of those measurements was considered to be the % WSA content for the epipedon. Soil pH was determined on a 2:1 water:soil paste with 5 g of soil (Soil Survey Staff, 1996). Soil particle size distribution was determined using the volumetric pipette procedure (Soil Survey Staff, 1996). Soil organic carbon was determined by the Iowa State Soil Testing Laboratory. Total organic carbon was measured with a Leco LC2000 (Model CHN 600, LECO, St. Joseph, MI). Samples with pH >7.5 were analyzed by acid injection (Sherrod et al., 2002) to determine inorganic carbon content. That value was subtracted from total carbon to obtain SOC values.
**Statistical Analysis**

Cores were grouped by land use, soil series map unit, and landscape position with the GIS software ArcGIS (ESRI Redlands, CA) (Table 1 and Figure 2). Soil series map unit polygons were obtained from the Iowa Cooperative Soil Survey (ICSS, 2003). Landscape positions were identified at sample locations in the field using the summit, shoulder, backslope, footslope, and toeslope model (Ruhe, 1975). GIS polygons were manually digitized using field classification along with slope and curvature derived from the DEMs using ArcGIS. Digital elevation models (DEM) were developed from vehicle based real time kinematic global position system (RTK-GPS) points gathered in each land use. RTK-GPS uses differential-GPS with carrier phase ambiguity resolution to achieve horizontal accuracies of <1 cm and vertical accuracies from 2 – 10 cm (CMT Z33 Operator’s Manual, 1997). A simple kriging procedure within ArcGIS was used to interpolate the elevation points to a 5m grid resolution. Soil map units, landscape positions, elevation, and slope are shown for both land uses in Figure 2. Samples were grouped by core horizons and diagnostic classes (epipedon and subsoil) for most analyses. Epipedons included all horizons with Munsell value and chroma <3. The subsoil included all horizons beneath the epipedon. Standard descriptive statistics, including means and standard errors, were used to evaluate each class using SAS 9.1 for Windows (SAS Institute Inc., Cary, NC). Soil series and landscape position class properties were calculated from all cores falling within that classes map unit boundary. Analysis of variance (ANOVA) was done to determine the ability of grouping schemes to explain soil property variance between soil series, landscape positions, and land use. The Brown – Forsythe test (1974) was performed to ensure homogeneity of variance. Significance was considered at the 0.05 level.
Analysis of variance (ANOVA) was done for three different data sets: all described cores, laboratory analyzed cores, and selected texture cores. Epipedon thickness, surface sample bulk density, elevation and slope were analyzed for all described cores. Laboratory analyzed cores were used to determine particle size distribution, SOC, pH, and WSA. These measurements, with the exception of particle size distribution, were averaged over the epipedon and subsoil of each core to provide a basis for comparisons between and within land uses. The particle size distribution of laboratory analyzed cores was done on surface horizons only. Epipedon thickness, bulk density, elevation, and slope were also analyzed in just these laboratory cores to provide information about bias due to the location of the selected nested grid. A selected set of cores, sixteen in each land use, were chosen for particle size analysis on all horizons. Significance tests within land uses test the model in which each soil property mean is equal to soil series or landscape position. This assesses how much of the property's variance is accounted for by soil series and landscape position differences. Significance tests between land uses by soil series and landscape position indicate the effect of land use on that property. The analysis of elevation and slope provides insight into the usefulness of the models in separating both landscape features.

**Results and Discussion**

Epipedon thickness is influenced by factors that vary greatly between these land uses. These factors include vegetation, bioturbation, compaction, erosion, and moisture conditions (Buol et al., 2003; Hole, 1981). The greater average epipedon thickness of the prairie (47.9 SE 1.2 cm) than the agricultural field (39.7 SE 0.8 cm) reflects the increased oxidation and erosion of surface materials that often occur with cultivation. These same factors also
influence bulk density. Surface horizon bulk density is significantly greater in the agricultural field (1.26 SE 0.02 g cm\(^{-3}\)) than the prairie (1.19 SE 0.02 g cm\(^{-3}\)).

Land use affects SOC content by changing the balance of inputs and removals of organic matter. Soil organic carbon content gains in terrestrial ecosystems are influenced by photosynthesis inputs from plants. Soil organic carbon is lost by increasing rates of decomposition or increasing losses to erosion (Bruce et al., 1999; Stevenson and Cole, 1999). Prairie epipedons have significantly greater soil organic carbon, SOC, content (32.57 SE 1.28 g kg\(^{-1}\), 30.87 SE 1.03 kg M\(^{-3}\)) than the agriculture field (21.29 SE 0.65 g kg\(^{-1}\), 28.40 SE 0.93 kg M\(^{-3}\)). The combination of disturbance from tillage implements and less root and microbial biomass can also reduce soil aggregate stability (Kay, 1995; Harris et al., 1966). The prairie has significantly greater % water stable aggregate (WSA) content than the field overall (agriculture (ag) 27.4 SE 1.72%, prairie (pr) 63.9 SE 1.8%; \(P = <0.0001\)).

Cultivation and vegetation can both impact soil pH, especially in surface horizons (Anderson, 1987; Richardson et al., 1985). In this study area, the pH of the agriculture field epipedon (5.9 SE 0.06 pH) is slightly but significantly greater than the prairie (5.2 SE 0.06 pH).

Cultivation alters erosion rates primarily through changes in land cover (Troeh, 1999; Gerrard, 1981). Erosion and sedimentation cause sorting of particle size fractions laterally across the landscape (Ruhe and Walker, 1968). Epipedons of each land use have significantly different contents of the particle size fractions medium sand (ag 11.7 SE 0.6%, pr 9.7 SE 0.8%), fine sand (ag 10.2 SE 1.5%, pr 6.8 SE 0.5%), total sand (ag 32.4SE 2.0%, pr 25.6 SE 2.0%), fine silt (ag 24.4 SE 1.0%, pr 27.0 SE 0.8%), and total clay (ag 22.8 SE 1.0%, pr 25.7 SE 0.8%). Across all analyzed core surface horizons, the agricultural field has
greater sand content and the prairie has greater silt content. While all but two fractions, fine silt and very coarse sand, are statistically significantly different between land uses, the differences are not of a large magnitude. The prairie has 4.2% greater coarse silt content and 2% less fine sand with no other fractions differing by more than 1.5%.

Soil Series

Cores were first grouped by soil series map units. Soil series refers to the map unit designation at the location of each core and does not reflect classification based on its own morphology. Map units of the same soil series, but differing in other characteristics (i.e. slope) were considered one soil series map unit. Because soil series are defined by a suite of soil properties, models used to delineate them capture the soil forming factors that control the distribution of soil properties. This analysis provides an example of using a widely used, easily available model for explaining the spatial distribution of soil properties.

Epipedon properties of all described cores along with the terrain attributes of elevation and slope were analyzed by soil series in Table 2. When individual soil series are compared between land uses, each soil series, with one exception, has significantly greater epipedon thickness in the prairie. Only the Clyde map unit epipedon is significantly thicker in the agricultural field (ag 64.4 SE 3.9cm, pr 45.5 SE 3.7 cm). This appears to be due to two factors: the location of the soil series map units themselves, and the location of the nested grid within the map units. The Clyde soil series occurs at mid-elevation positions in the prairie and at the lowest elevation in the agricultural field (Figure 2). The prairie soil series map does not follow the general catena concept for the Cresco-Floyd-Clyde soil association mapped in this area in which Clyde occurs at the lowest elevations (Buckner et al., 1974). However, the soil cores taken within the Clyde map unit boundary of the prairie meet the
taxonomic classification criteria for the Clyde soil series at the same rate as those in the agricultural field. In addition to differences in soil series mapping locations, there are differences in the placement of cores within those soil series due to our randomly selected nested grid sampling scheme. In the agricultural field Clyde soil series, the area of lowest elevation, with the thickest epipedon, was more heavily sampled than the higher elevation, thinner epipedon areas of the same map unit. Within each land use, soil series account for a significant portion of the variability in epipedon thickness. We would expect epipedon thickness to be related to soil series because epipedon thickness itself is used in determining and separating soil series.

Bulk densities are significantly different between land uses for only one soil series. In the Floyd series, bulk density is significantly greater in the agricultural field, 1.31 SE 0.04 g cm$^{-3}$, than in the prairie, 1.13 SE 0.04g cm$^{-3}$. Soil series are not significantly different in mean bulk density within either the agricultural field or the prairie.

Soil map units are delineated by extrapolating across landscapes using topography as a guide. Thus, we would expect soil series to occupy areas with different, although overlapping, topographic features. Both the slope (ag 3.5% SE 0.12, pr 1.6% SE 0.04) and elevation (ag 383.4 SE 0.2 m, pr 387.0 SE 0.3 m) at sample locations are significantly different for soil series within each land use (Table 3). Elevation is significantly greater in the prairie for three of the five soil series sampled in each land use (note previous discussion of Clyde soil series). Slope is significantly greater in the agricultural field for all of the soil series. These differences between land use elevation and slope confound the comparison of soil properties between land uses by soil series. To test the influence of elevation and slope on property distribution, a regression analysis was performed between elevation and slope
and all other measured variables. No properties were significant for their regression with slope. Only two factors had significant relationships with elevation and those were weak, epipedon thickness ($r^2 = 0.04$) and bulk density ($r^2 = 0.02$).

For laboratory cores, epipedon averages of thickness, bulk density, soil organic carbon (SOC) content, water stable aggregate (WSA) content, and pH are given by soil series in Table 3. When individual soil series SOC contents are compared between land uses, only two (Clyde and Cresco) are significant on a weight per weight basis and none on a weight per volume basis. Within each land use, SOC content on a weight per weight basis (g kg$^{-1}$) is significantly different between soil series in the prairie ($P < 0.0001$) but not in the agricultural field ($P = 0.4965$). However, when considered on a weight per volume basis, neither land use has significantly different soil series means ($ag P = 0.8664, pr P = 0.0544$). Neither land use has significant differences in subsoil SOC content in either measurement. The prairie has significantly greater % WSA content than the field overall and for each individual soil series. Within each land use, soil series are not significantly different for either land use in % WSA. pH was significantly greater in the agricultural portion of the Cresco, Floyd, and Protivin soil series. Within each land use, soil series do not have significantly different pHs in the epipedon ($ag P = 0.6718, pr P = 0.3904$). The subsoil has significantly different pH in the prairie ($P = 0.0004$), but not in the agriculture field ($P = 0.3699$).

The surface horizons of laboratory cores showed few differences in texture between soil series and land uses (Table 4). Only 10 soil series-particle size class combinations are significantly different between land uses out of the 50 combinations that were analyzed. Six of these occur in the Cresco soil series, where a sand lens was present in the glacial till.
Within the agricultural field, soil series are not significantly different for any of the size fractions. Soil series within the prairie are significantly different in all except the very fine sand fractions. This difference in particle size analysis indicates that the distribution of particle size classes is fundamentally different in each land use. The differing particle size distributions of surface horizons may be due to greater inherent variability in the prairie and surface soil homogenization by tillage in the agricultural field.

The epipedon thicknesses of the subset of cores chosen for laboratory analysis show different trends than the analysis of all described cores (Tables 2 and 3). In this analysis, the Clyde soil series are not significantly different in epipedon thickness between land uses. Within each land use, thickness is significant in the agricultural field (P= 0.0137) but not in the prairie (P= 0.1356). The analysis of the laboratory cores leads to a completely different conclusion about the distribution of bulk density among soil series. In the full dataset analysis, only one soil series was significantly different between land uses. In the analysis of this subset of cores, the agricultural field has greater bulk density for every soil series except Protivin. Within land uses, bulk density is significantly different among soil series in the agricultural field (P= 0.0493) but not in the prairie (P= 0.2184). While elevation is still significant for both land uses, slope is not significant in the prairie. These differences between all cores and analyzed cores indicate that the selection of the laboratory analyzed cores may be influencing the results of our analysis.

The analysis of the cores selected for full texture analysis show very little difference for soil series either within or between land uses. When the overall average particle size distributions for each land use are compared, epipedons are significantly different for several particle size fractions. When individual soil series are compared, there are only two
significantly different fractions. In the Cresco soil series of the agricultural field, epipedons have 0.5% less very fine sand (fraction b) and 5.5% more very fine silt than prairie epipedons. The lack of statistically significant differences for all other soil series and fractions indicates that the difference in average land use texture is due to the differing extents of soil map units and inherent variability within each land use. Within each land use, only fine silt is significantly different between soil series epipedons. The particle size fractions in the subsoil were only significantly different for soil series clay within the prairie ranging from 20% in the Ostrander series to 31% in the Cresco series.

**Landscape Position**

Cores were next grouped by landscape position; summit, shoulder, backslope, and footslope. Landscape position is often described according to Ruhe’s (1975) model, but it is not generally mapped and used directly in GIS manipulations. By testing the model of soil property equal to landscape position, we can assess how much of the properties variability is controlled by topography as described in this simple landscape model.

Epipedon thickness and surface sample bulk density of all described cores are given by landscape position in Table 5. Once again elevation and slope are analyzed to provide insight into the usefulness of the landscape model in describing terrain attributes. The prairie has significantly greater epipedon thickness in all landscape positions except footslopes. Within each land use, landscape positions account for a significant portion of the variance in epipedon thickness (ag \( P = 0.0001 \), pr \( P = 0.0011 \)). Epipedon thickness has been shown to be related to landscape position because of the erosional and hydrologic differences between landscape positions (Young and Hammer, 2000). For instance, we would expect backslopes with high surface runoff to have more erosion and less available moisture than a concave
footslope where sediment might deposit and moisture collect, creating a thicker epipedon. Following this logic, increased erosion in upslope positions of the agricultural field would lead to increased deposition in footslope positions. This would corroborate our findings that footslope epipedons were not significantly different for the agriculture field and the prairie. In addition, the footslope samples in the agriculture field coincide with the Clyde soil series that is thicker in the agricultural field. However, we do not have evidence of deposition such as particle size sorting or buried A horizon. In the absence of morphology and particle size data that indicate increased deposition in the agriculture field, we conclude that the location of the nested grid in the agriculture field is biasing the mean values of epipedon thickness for these classes.

Bulk density is significantly different between land uses only for footslopes; agriculture 1.34 g cm$^{-3}$ and prairie 1.14 g cm$^{-3}$. Within land uses, bulk density is not significant across landscape positions in either the agricultural field (P= 0.1026) or the prairie (P= 0.3449). No effort was made to control for implement tracks or inter-row variability in the agriculture field or gopher mounds and vegetation in the prairie. The variation in site characteristics affecting bulk density within each landscape position mostly likely obscures any difference between landscape positions. Each landscape position has significantly greater elevation in the prairie (4.5m on average) and significantly greater slope in the agriculture field (2% on average). While landscape positions also have significantly different slopes within each land use, the average slope of each landscape position only ranges 2.8% in the agriculture field and 0.5% in the prairie.

The landscape position epipedon properties of laboratory analyzed cores along with the terrain attributes of elevation and slope are shown in Table 5. The prairie has
significantly greater SOC content on a weight per weight basis (g kg\(^{-1}\)) in backslopes, footslopes, and shoulders. Within land uses, SOC content on a weight per weight basis (g kg\(^{-1}\)) is not significantly different between landscape positions for either the prairie or the agricultural field. When SOC content is considered on a weight per volume basis, no landscape position is significantly different between land uses, nor are landscape positions significantly different within land uses. This is in contrast to previous studies such as Pennock et al. (1994), Gessler et al. (2000) and Young and Hammer (2000) that show a strong correlation between SOC content and landscape positions. This may be due to the relatively low relief of this study site, and the area in general. The Iowa Surface is characterized by generally long, low grade slopes (Prior, 1990). This landscape position model was developed in more deeply dissected areas and it may not adequately separate this more subtle landscape into functionally different units.

While the prairie had significantly greater % WSA content for all landscape positions and lower pH for each position except the summits, landscape position epipedons were not significantly different within land uses in either % WSA content or pH. In contrast to the soil map unit analysis, subsoil pHs were significantly different between landscape position in the agriculture field (P=<0.0171), but not in the prairie (P=0.8531).

Once again, analyzing just those cores chosen for laboratory analyses gives us somewhat different results. The epipedon thickness of just the laboratory analyzed cores is significantly greater in the prairie for footslopes and summits. Landscape position within land uses are significantly different in neither the agricultural field (P= 0.2548) or the prairie (P= 0.2089). The analyzed core bulk density is significantly greater in the agricultural field for all landscape positions. However, bulk density is not significantly different within either
land use (ag P= 0.5054, pr P= 0.2664). While elevation of this subset is significant within both land uses, slope is not significant between landscape positions in the prairie. Once again, the differences between all cores and analyzed cores indicate that the location of the cores selected for laboratory analysis may be biasing our analyses.

Particle size distribution in surface horizons of all laboratory cores is shown by landscape position in Table 6. When land uses are compared by landscape position, there are greater differences than there were within soil map units. Backslopes, footslopes, and summits have similar particle size differences. In backslope positions, the prairie has significantly more very fine sand (fraction a) and significantly less coarse silt. Prairie footslopes have significantly greater amounts of fine and very fine sand fractions with significantly less coarse silt. Summits have greater fine sand and very fine sand fractions in the prairie. Shoulder positions, in contrast, are significantly different between land uses for all sand and silt fractions except very fine sand (fraction b). Within the agricultural field, there are no fractions that are significantly different between land uses. The prairie has significant differences between landscape positions for very coarse sand, coarse sand, very fine sand (b) and clay particle size classes. Landscape positions account for less of the agricultural field variability in particle size distribution.

When the cores selected for full texture determination are analyzed, there are a few differences within and between landscape positions for the average particle size fractions of epipedons and subsoils. Particle size fractions of epipedons are significantly different between land uses for only the very coarse sand fraction of shoulders. The difference is only 0.1%, and not likely to be pedologically significant. No fraction is significantly different for landscape position epipedons within each land use. For the subsoil, total sand is significantly
different between landscape positions in the agricultural field (P= 0.0200) with a range from 37% sand in summits and backslopes to 55% sand in footslopes. Clay content is significantly different within the prairie (P= 0.0500) and ranges from 24% in footslopes to 33% in backslopes. Subsoil texture is not likely to have been changed by land use and reflects the inherent variability of the landscape.

Conclusions

Soil series and landscape position can be used to ascertain the spatial distribution of soil properties across this landscape. In this study we used ANOVA within an agricultural field and a native prairie to determine soil property distribution using soil series map units and landscape positions. Soil series map units partitioned more properties into significantly different classes than landscape positions did. Soil series were significantly different within both land uses for epipedon thickness, elevation, and slope. Several particle size fractions and SOC content were significantly different among soil series within the prairie. Landscape positions were significantly different in epipedon thickness and elevation within the agricultural field and prairie, and pH only in the prairie. The larger extent of landscape positions encompass greater variation within each class and do not differ as greatly from one another as soil series do. Comparing land uses, the prairie has slightly more stratification of soil properties between these soil classes.

Analysis of variance on individual classes between land uses was also used to examine the effect of land uses on soil properties. When comparing individual soil series, prairies consistently have significantly greater epipedon thickness and % WSA content and lower epipedon bulk density. There are some individual soil series that do not follow these trends, such as Clyde in epipedon thickness, and Protivin in bulk density. Landscape
positions in the prairie have greater SOC content by weight, greater % WSA content, lower pH and lower bulk density.

Overall, this analysis shows that prairies have greater epipedon thickness, greater % WSA content and lower bulk density. The greater number of significant differences within the prairie also indicates that its soil properties are generally more ordered than the agriculture field. The map unit classes used and the selection of core locations affect the conclusions that will be drawn.

References


Table 1. Number of cores taken in each soil series map unit and landscape position.

<table>
<thead>
<tr>
<th>Soil Series†</th>
<th>Great Group</th>
<th>All Cores</th>
<th>Laboratory Cores</th>
</tr>
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<tbody>
<tr>
<td></td>
<td></td>
<td>Agriculture</td>
<td>Prairie</td>
</tr>
<tr>
<td>Clyde</td>
<td>Typic Endoaquoll</td>
<td>32</td>
<td>11</td>
</tr>
<tr>
<td>Cresco</td>
<td>Typic Argiudoll</td>
<td>87</td>
<td>88</td>
</tr>
<tr>
<td>Floyd</td>
<td>Aquic Hapludoll</td>
<td>31</td>
<td>38</td>
</tr>
<tr>
<td>Jameston</td>
<td>Typic Argiaquolls</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Kenyon</td>
<td>Typic Hapludoll</td>
<td>2</td>
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<tr>
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<td>Typic Hapludoll</td>
<td>35</td>
<td>30</td>
</tr>
<tr>
<td>Protivin</td>
<td>Aquic Argiudoll</td>
<td>14</td>
<td>13</td>
</tr>
<tr>
<td>Schley</td>
<td>Udollic Endoaqualf</td>
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<table>
<thead>
<tr>
<th>Landscape Position‡</th>
</tr>
</thead>
<tbody>
<tr>
<td>Summit</td>
</tr>
<tr>
<td>Shoulder</td>
</tr>
<tr>
<td>Backslope</td>
</tr>
<tr>
<td>Footslope</td>
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</tbody>
</table>

† Soil series and great group as identified by the Iowa Cooperative Soil Survey digital data (2001).
‡ Landscape position identified in the field according to Ruhe’s (1975) model.
Table 2. Epipedon property means for all cores taken by soil series map unit in each land use.

<table>
<thead>
<tr>
<th>Property</th>
<th>Clyde</th>
<th>Cresco</th>
<th>Floyd</th>
<th>Jameston</th>
<th>Kenyon</th>
<th>Ostrander</th>
<th>Protivin</th>
<th>Schley</th>
<th>P &gt; f†</th>
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</thead>
<tbody>
<tr>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>&lt;0.0001</td>
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<tr>
<td>Ag</td>
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<td>39.5</td>
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<td>54.4</td>
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<td>55.1</td>
<td>47.8</td>
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<td></td>
<td>&lt;0.0001</td>
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<tr>
<td>Bulk Density g cm²</td>
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<td></td>
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<tr>
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<td>1.22</td>
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<td>1.18</td>
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<td></td>
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<td>388.3</td>
<td>394.5</td>
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<td>Slope, %</td>
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<td></td>
<td></td>
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<td>Pr</td>
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<td>1.7</td>
<td>1.3</td>
<td>2.0</td>
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<td>1.8</td>
<td></td>
<td>&lt;0.0001</td>
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</tr>
</tbody>
</table>

† P>F is for ANOVA of soil series classes within each land use.
‡ Thickness refers to thickness of the epipedon determined in this case by the presence of mollic colors (Soil Taxonomy, 1999).
§ Ag, agricultural field; Pr, prairie.
Table 3. Epipedon property means of laboratory analyzed cores for soil series map unit in each land use.

<table>
<thead>
<tr>
<th>Property</th>
<th>Clyde</th>
<th>Cresco</th>
<th>Floyd</th>
<th>Jameston</th>
<th>Kenyon</th>
<th>Ostrander</th>
<th>Protivin</th>
<th>Schley</th>
<th>P &gt; F</th>
</tr>
</thead>
<tbody>
<tr>
<td>Thickness cm</td>
<td>Ag</td>
<td>54.0</td>
<td>33.7</td>
<td>39.6</td>
<td>39.5</td>
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<td>53.0</td>
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<td>53.5</td>
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<td>Bulk Density g cm^-3</td>
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<td>1.36</td>
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<td>1.32</td>
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<td>20.46</td>
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<tr>
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<td>26.16</td>
<td>26.32</td>
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<td>30.77</td>
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<td>5.8</td>
<td>5.8</td>
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<td>6.0</td>
<td>6.0</td>
<td>6.5</td>
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</tr>
<tr>
<td></td>
<td>Pr</td>
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<td>5.1</td>
<td>5.1</td>
<td>5.8</td>
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<td>5.1</td>
<td></td>
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<td>26.9</td>
<td>34.1</td>
<td>30.1</td>
<td>27.7</td>
<td>28.6</td>
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</tr>
<tr>
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<td>Pr</td>
<td>67.9</td>
<td>63.1</td>
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<td>389.0</td>
<td>388.3</td>
<td>391.8</td>
<td>385.6</td>
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</tr>
<tr>
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<td>Pr</td>
<td>391.4</td>
<td>394.5</td>
<td>389.8</td>
<td>393.6</td>
<td>388.1</td>
<td>394.4</td>
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<td>&lt;0.0001</td>
</tr>
<tr>
<td>Slope %</td>
<td>Ag</td>
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<td>3.0</td>
<td>3.3</td>
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<td>1.4</td>
<td>1.8</td>
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<td>1.8</td>
<td></td>
<td>0.0058</td>
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</tbody>
</table>

‡ P>F is for ANOVA of soil series classes within each land use.
‡ Thickness refers to thickness of the epipedon determined in this case by the presence of mollic colors (Soil Taxonomy, 1999).
§ Ag, agricultural field; Pr, prairie; SOC, soil organic carbon; WSA, water stable aggregate content.
Table 4. Particle size distribution for the surface horizons of analyzed cores in each land use and soil series map unit.

<table>
<thead>
<tr>
<th>Fraction (mm)</th>
<th>Clyde</th>
<th>Cresco</th>
<th>Floyd</th>
<th>Jameston</th>
<th>Kenyon</th>
<th>Ostrander</th>
<th>Protivin</th>
<th>Schley</th>
<th>P&gt;F†</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Very coarse sand</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(2.0 - 1.0)</td>
<td>Ag‡</td>
<td>0.8</td>
<td>0.9</td>
<td>0.8</td>
<td>0.5</td>
<td>0.8</td>
<td>0.8</td>
<td>1.7</td>
<td>0.0977</td>
</tr>
<tr>
<td></td>
<td>Pr</td>
<td>2.0</td>
<td>0.6</td>
<td>1.0</td>
<td>0.5</td>
<td>1.6</td>
<td>0.4</td>
<td></td>
<td>0.0088</td>
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<tr>
<td><strong>Coarse sand</strong></td>
<td>Ag</td>
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<td>4.0</td>
<td>4.3</td>
<td>3.8</td>
<td>4.6</td>
<td>4.4</td>
<td>6.7</td>
<td>0.1187</td>
</tr>
<tr>
<td>(1.0 - 0.5)</td>
<td>Pr</td>
<td>3.5</td>
<td>3.4</td>
<td>5.5</td>
<td>3.4</td>
<td>5.6</td>
<td>3.4</td>
<td></td>
<td>0.0016</td>
</tr>
<tr>
<td><strong>Medium sand</strong></td>
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<td>9.8</td>
<td>10.4</td>
<td>9.3</td>
<td>11.5</td>
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<td>14.6</td>
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</tr>
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<td>(0.5 - 0.25)</td>
<td>Pr</td>
<td>5.7</td>
<td>8.9</td>
<td>11.6</td>
<td>8.6</td>
<td>12.7</td>
<td>8.3</td>
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<td>&lt;0.0001</td>
</tr>
<tr>
<td><strong>Fine sand</strong></td>
<td>Ag‡</td>
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<td>8.5</td>
<td>7.2</td>
<td>11.0</td>
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<td>(0.25 - 0.125)</td>
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<td>3.9</td>
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<td>5.9</td>
<td>8.2</td>
<td>5.6</td>
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<tr>
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<td>3.9</td>
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<td>2.6</td>
<td>3.4</td>
<td>3.2</td>
<td>3.4</td>
<td>0.6676</td>
</tr>
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<td>(0.125 - 0.063)</td>
<td>Pr</td>
<td>2.0</td>
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<td>2.6</td>
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<td>2.6</td>
<td></td>
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</tr>
<tr>
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<td>0.8</td>
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<td>0.6</td>
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<td>0.7</td>
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</tr>
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<td>(0.063 - 0.053)</td>
<td>Pr</td>
<td>0.6</td>
<td>0.7</td>
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<td>30.2</td>
<td>25.6</td>
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<td>29.7</td>
<td>26.9</td>
<td>38.0</td>
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<td>(2.0 - 0.053)</td>
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<td>21.7</td>
<td>31.6</td>
<td>21.0</td>
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</tr>
<tr>
<td><strong>Coarse Silt</strong></td>
<td>Ag‡</td>
<td>23.2</td>
<td>22.2</td>
<td>21.0</td>
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<td>22.1</td>
<td>20.3</td>
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<td>Pr</td>
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<td>26.3</td>
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<td>27.1</td>
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<td>26.6</td>
<td>27.7</td>
<td>21.5</td>
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<tr>
<td>(0.020 - 0.002)</td>
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<td>27.1</td>
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<td>24.6</td>
<td>25.2</td>
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<tr>
<td><strong>Total Silt</strong></td>
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<td>45.2</td>
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<td>50.1</td>
<td>47.7</td>
<td>47.2</td>
<td>42.6</td>
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</tr>
<tr>
<td>(0.053 - 0.002)</td>
<td>Pr</td>
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<td>50.1</td>
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<td>49.9</td>
<td>47.5</td>
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<tr>
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<td>Ag‡</td>
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<td>25.1</td>
<td>24.6</td>
<td>24.9</td>
<td>21.5</td>
<td>25.1</td>
<td>19.8</td>
<td>0.1916</td>
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<tr>
<td>(&lt;0.002)</td>
<td>Pr</td>
<td>23.9</td>
<td>26.2</td>
<td>24.1</td>
<td>27.3</td>
<td>21.1</td>
<td>25.8</td>
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† P>F is for ANOVA of soil series classes within each land use.
‡ Ag, agricultural field; Pr, prairie.
Table 5. Epipedon property means for landscape positions in each land use.

<table>
<thead>
<tr>
<th></th>
<th>Backslope</th>
<th>Footslope</th>
<th>Shoulder</th>
<th>Summit</th>
<th>P&gt;f†</th>
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</thead>
<tbody>
<tr>
<td><strong>All Cores</strong></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Thickness cm‡</td>
<td>Ag§</td>
<td>40.6</td>
<td>53.4</td>
<td>34.7</td>
<td>26.9</td>
</tr>
<tr>
<td></td>
<td>Pr</td>
<td>46.2</td>
<td>51.8</td>
<td>41.6</td>
<td>43.8</td>
</tr>
<tr>
<td>Bulk Density g cm⁻³</td>
<td>Ag</td>
<td>1.21</td>
<td>1.34</td>
<td>1.26</td>
<td>1.29</td>
</tr>
<tr>
<td></td>
<td>Pr</td>
<td>1.23</td>
<td>1.14</td>
<td>1.21</td>
<td>1.20</td>
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<td>Elevation m</td>
<td>Ag</td>
<td>389.6</td>
<td>386.9</td>
<td>390.4</td>
<td>389.6</td>
</tr>
<tr>
<td></td>
<td>Pr</td>
<td>393.6</td>
<td>389.8</td>
<td>395.1</td>
<td>396.2</td>
</tr>
<tr>
<td>Slope %</td>
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<td>3.1</td>
<td>4.2</td>
<td>2.4</td>
</tr>
<tr>
<td></td>
<td>Pr</td>
<td>1.8</td>
<td>1.3</td>
<td>1.7</td>
<td>1.6</td>
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<td><strong>Laboratory Cores</strong></td>
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<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Thickness cm</td>
<td>Ag</td>
<td>40.8</td>
<td>39.9</td>
<td>34.8</td>
<td>31.0</td>
</tr>
<tr>
<td></td>
<td>Pr</td>
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<tr>
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<td>1.38</td>
<td>1.41</td>
<td>1.34</td>
</tr>
<tr>
<td></td>
<td>Pr</td>
<td>1.05</td>
<td>1.07</td>
<td>1.06</td>
<td>1.08</td>
</tr>
<tr>
<td>SOC g kg⁻³</td>
<td>Ag</td>
<td>22.14</td>
<td>22.88</td>
<td>20.50</td>
<td>18.92</td>
</tr>
<tr>
<td></td>
<td>Pr</td>
<td>32.47</td>
<td>34.35</td>
<td>36.82</td>
<td>28.71</td>
</tr>
<tr>
<td>SOC kg m⁻³</td>
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<td>28.78</td>
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<td>33.63</td>
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<tr>
<td>pH</td>
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<td>6.1</td>
<td>5.9</td>
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<tr>
<td></td>
<td>Pr</td>
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<td>5.5</td>
<td>5.4</td>
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</tr>
<tr>
<td>WSA %</td>
<td>Ag</td>
<td>32.5</td>
<td>27.2</td>
<td>24.9</td>
<td>17.8</td>
</tr>
<tr>
<td></td>
<td>Pr</td>
<td>67.1</td>
<td>61.5</td>
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<td>387.0</td>
<td>391.0</td>
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<tr>
<td>Slope %</td>
<td>Ag</td>
<td>3.2</td>
<td>2.3</td>
<td>3.4</td>
<td>2.4</td>
</tr>
<tr>
<td></td>
<td>Pr</td>
<td>1.7</td>
<td>1.4</td>
<td>1.7</td>
<td>1.6</td>
</tr>
</tbody>
</table>

† P>F is for ANOVA of soil series classes within each land use.
‡ Thickness refers to thickness of the epipedon determined in this case by the presence of mollic colors (Soil Taxonomy, 1999).
§ Ag, agricultural field; Pr, prairie; SOC, soil organic carbon; WSA, water stable aggregate content.
Table 6. Particle size distribution for the surface horizon of analyzed cores in each land use and landscape position as percent of total mineral matter.

<table>
<thead>
<tr>
<th>Fraction (mm)</th>
<th>Backslope</th>
<th>Footslope</th>
<th>Shoulder</th>
<th>Summit</th>
<th>P&gt;(f)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Ag</td>
<td>Pr</td>
<td>Ag</td>
<td>Pr</td>
<td></td>
</tr>
<tr>
<td>Very coarse sand</td>
<td>0.8</td>
<td>0.7</td>
<td>0.8</td>
<td>0.9</td>
<td>0.7650</td>
</tr>
<tr>
<td>(2.0 - 1.0)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Coarse sand</td>
<td>3.9</td>
<td>4.2</td>
<td>4.5</td>
<td>3.9</td>
<td>0.1430</td>
</tr>
<tr>
<td>(1.0 – 0.5)</td>
<td>3.5</td>
<td>4.6</td>
<td>2.9</td>
<td>3.7</td>
<td>0.0488</td>
</tr>
<tr>
<td>Medium sand</td>
<td>9.3</td>
<td>10.7</td>
<td>10.8</td>
<td>10.2</td>
<td>0.1184</td>
</tr>
<tr>
<td>(0.5 – 0.25)</td>
<td>9.0</td>
<td>9.7</td>
<td>7.9</td>
<td>9.2</td>
<td>0.4527</td>
</tr>
<tr>
<td>Fine sand</td>
<td>8.2</td>
<td>11.0</td>
<td>7.7</td>
<td>7.3</td>
<td>0.3339</td>
</tr>
<tr>
<td>(0.25 – 0.125)</td>
<td>6.2</td>
<td>6.3</td>
<td>5.6</td>
<td>6.4</td>
<td>0.6774</td>
</tr>
<tr>
<td>Very fine sand a</td>
<td>3.2</td>
<td>3.5</td>
<td>3.5</td>
<td>3.5</td>
<td>0.5027</td>
</tr>
<tr>
<td>(0.125 – 0.063)</td>
<td>2.8</td>
<td>2.5</td>
<td>2.7</td>
<td>3.0</td>
<td>0.1017</td>
</tr>
<tr>
<td>Very fine sand b</td>
<td>0.8</td>
<td>0.8</td>
<td>0.7</td>
<td>1.0</td>
<td>0.3667</td>
</tr>
<tr>
<td>(0.063 – 0.053)</td>
<td>0.7</td>
<td>0.6</td>
<td>0.7</td>
<td>0.8</td>
<td>0.0236</td>
</tr>
<tr>
<td>Total Sand</td>
<td>26.2</td>
<td>30.9</td>
<td>28.1</td>
<td>26.6</td>
<td>0.5022</td>
</tr>
<tr>
<td>(2.0 - 0.053)</td>
<td>22.8</td>
<td>24.9</td>
<td>20.1</td>
<td>23.9</td>
<td>0.3090</td>
</tr>
<tr>
<td>Coarse Silt</td>
<td>22.2</td>
<td>21.3</td>
<td>21.1</td>
<td>22.7</td>
<td>0.6232</td>
</tr>
<tr>
<td>(0.053 - 0.020)</td>
<td>25.4</td>
<td>25.3</td>
<td>25.7</td>
<td>24.0</td>
<td>0.7180</td>
</tr>
<tr>
<td>Fine Silt</td>
<td>26.8</td>
<td>25.4</td>
<td>26.2</td>
<td>27.2</td>
<td>0.7169</td>
</tr>
<tr>
<td>(0.020 - 0.002)</td>
<td>25.4</td>
<td>25.9</td>
<td>28.2</td>
<td>25.7</td>
<td>0.2539</td>
</tr>
<tr>
<td>Total Silt</td>
<td>48.4</td>
<td>45.6</td>
<td>46.2</td>
<td>50.0</td>
<td>0.2694</td>
</tr>
<tr>
<td>(0.053 - 0.002)</td>
<td>50.2</td>
<td>50.9</td>
<td>53.3</td>
<td>48.2</td>
<td>0.2842</td>
</tr>
<tr>
<td>Total Clay</td>
<td>24.8</td>
<td>22.4</td>
<td>24.6</td>
<td>23.5</td>
<td>0.2811</td>
</tr>
<tr>
<td>(&lt;0.002)</td>
<td>26.3</td>
<td>23.9</td>
<td>25.9</td>
<td>26.3</td>
<td>0.0147</td>
</tr>
</tbody>
</table>

\* P>\(F\) is for ANOVA of landscape classes within each land use.
\* Ag, agricultural field; Pr, prairie.
Figure 1. Location of study site on the Iowan Surface in northeastern Iowa, USA. Locations of all described cores, laboratory analyzed cores, and selected texture cores are shown on an aerial photograph.
Figure 2. Digital elevation model and slope position as derived from RTK-GPS data using ArcGIS overlain with soil series map units (Iowa Cooperative Soil Survey, 2003) and manually digitized landscape positions for the agriculture field, AG, and prairie, PR.
CHAPTER 3. SPATIAL ANALYSIS OF SOIL PROPERTIES USING GEOSTATISTICS

A paper to be submitted to Soil Science Society of America Journal

S.A. Wills, C.L. Burras, and J.A. Sandor

Abstract

While the use of geostatistics to model soil properties has been established for decades, there are few studies that use them to evaluate differences across land uses. The purpose of this study is to use geostatistics to compare the spatial distribution of soil properties in a native prairie and an agricultural field. Hayden Prairie State Preserve and an adjacent agricultural field were sampled in an unbalanced hierarchical nested grid for a total of 203 cores in each land use. Standard techniques were used to describe all cores and analyze a subset (63 cores in each land use) for soil organic carbon (SOC), % water stable aggregates (WSA), pH, and surface horizon particle size distribution. Standard spherical semi-variogram models were found to do the best job of modeling soil properties in both land uses. pH, WSA, and bulk density were not shown to be spatially dependent for either land use. The models for epipedon thickness have a nugget:sill ratio of 0.3 in the agricultural field and 1.1 in the prairie. SOC measurements (g kg$^{-1}$) were found to be spatially dependent in the agriculture field (n:s = 0.3), but not in the prairie (n:s = 1.0). Nearly all particle size fractions were spatially dependent for both land uses (n:s < 0.5). This indicates that the spatial distribution of SOC has been influenced by land use while particle size distribution has not. Overall, these models indicate that the soil properties of the agricultural field have greater spatial dependence, as measured by nugget:sill ratio(n:s), than the prairie.
Introduction

Geostatistics are a branch of statistics dealing with spatial phenomena in the earth sciences. Although geostatistics were initially developed to describe the spatial variability in ore deposits, they can be used to analyze any feature that exhibits spatial dependence (Webster and Oliver, 2001; Journel and Huijbrechts, 1978; Matheron, 1963). Geostatistics rest on the principle that things that are closer together are more alike than things that are farther apart. This central theme of geostatistics is known as the regionalized variable theory and the complementary function is known as a semi-variogram (Burgess and Webster, 1980a). Kriging uses the semi-variogram to predict values at unobserved location using minimization of errors (Krige, 1966). These principles have been applied to soil science for over two decades (e.g. Burgess and Webster, 1980a,b; Webster and Burgess, 1980). New computer applications have allowed more wide-spread development and use of geostatistical techniques. However, there are still many applications of geostatistics that have not yet been explored. The purpose of this study is to use geostatistics to evaluate and compare the spatial distribution of soil properties in a native prairie and agriculture field.

Agriculture homogenizes soil properties through direct and indirect means. Tillage homogenizes soil directly through mixing. Agriculture drainage reduces relative differences in soil moisture regimes. Cultivation has been shown to decrease the variability of soil organic carbon (SOC) (Cattle, 1994) and increase the maximum distance of spatial dependence for SOC and other properties (Cambardella et al., 1994; Robertson et al., 1993). In Spain, Paz-González et al. (2000) found that the distribution of soil properties under natural vegetation had a pure nugget effect. In that study, cultivated soils were found to be more homogeneous, with increased small scale continuity (reducing nugget effects) of
organic matter and cation exchange capacity. This study seeks to expand on these previous finding by using a greater number and size of samples in related but unstudied land uses.

**Materials and Methods**

**Study Area**

The study sites are on the Hayden State Prairie Preserve and an adjacent agricultural field in northeast Iowa (Figure 1). Most of the soils in this area are formed in one to two meters of Iowan Surface pedisement, which overlies a thick, dense Pre-Illinoian glacial till (Ruhe, 1969; Prior, 1991). Tallgrass prairie was the native vegetation for the past 8,000 to 9,000 years (Thompson, 1992). Soils formed from this combination of the Iowan Surface deposits and tallgrass prairie are extensive in Iowa and southeastern Minnesota, with more than 80% of the area currently dedicated to row crop production (Iowa Department of Natural Resources, 2000). Hayden Prairie is perhaps the only remaining large prairie remnant on the Iowa Surface while the cropped field represents the area’s predominant land use. The prairie and field provide an ideal contrast to evaluate the effects of a century worth of agricultural cultivation on soil property distribution.

**Sampling**

Each land use was sampled in an unbalanced hierarchical nested grid. This was done to determine the scale of spatial dependence and improve sampling efficiency (Borgelt et al., 1997; Oliver and Webster, 1986). A square grid was created and georeferenced to minimize the number of samples while assuring a range of spatial scales. A 24 ha area of both the prairie and agricultural field was divided into a 100m grid. This grid was separated into 6 blocks. Within each block, one 100m square was randomly selected for further division into
a nested grid. Each nested grid was composed of grid points that were 50, 25, 12.5, 5, and 2.5m apart (Figure 1). Cores (0.05m x 1.5m) were taken at each grid node with a truck mounted Giddings hydraulic soil probe. There were a total of 203 cores taken in each land use. Sixty-three of those cores were analyzed for soil organic carbon (SOC) content, pH, water stable aggregate (WSA) content.

**Field Description**

All 406 sampled cores were described and analyzed for bulk density. Field descriptions were done using standard techniques and nomenclature (Schoenberger et al., 2002). Bulk density was done on horizons and predetermined depth increments of 0-5, 5-10, 15-30, 30-50, and 50-100cm for each core. A portion of each horizon and depth increment was cut, weighed, and oven dried to determine bulk density by a modified volumetric core method (Konen, 1999; Soil Survey Staff, 1996).

**Laboratory Analysis**

Laboratory analyses were done on the samples from 100m grid cores and one randomly selected nested grid from each land use (63 cores from each land use). These cores will be referred to from this point on as laboratory cores. These analyses included pH, soil organic carbon, chroma meter color, water stable aggregate content, and surface horizon texture (Soil Survey Staff, 1996). A subset of these cores chosen to represent all landscape positions were also analyzed for particle size distribution. Samples were divided by horizon and depth increment for each core analyzed. Samples were ground to pass a 2mm sieve for further analysis. Chroma Meter color was used to determine Munsell hue, value and chroma for moist and dry ground samples as described under laboratory analysis (Konen et al.,
Percent water stable aggregate (WSA) content was determined on samples of depth increments 0-5, 5-10, and 15 cm to the bottom of the epipedon. Aggregates having 0.5 - 1 mm diameters were wet and sieved as outlined by the Soil Survey Staff (1996). The average of those measurements was considered to be % WSA content for the epipedon. Soil pH was determined on a 2:1 water:soil paste with 5 g of soil (Soil Survey Staff, 1996). Soil particle size distribution was determined using the volumetric pipette procedure (Soil Survey Staff, 1996). Soil organic carbon was determined by the Iowa State Soil Testing Laboratory. Total organic carbon was measured with a Leco LC2000 (Model CHN 600, LECO, St. Joseph, MI). Samples with pH >7.5 were analyzed by acid injection (Sherrod et al., 2002) to determine inorganic carbon content. That value was subtracted from total carbon to arrive at the SOC values.

** Statistical Analysis

Digital elevation models (DEM) were developed from points gathered with a vehicle based real time kinematic global position system (RTK-GPS) in each land use. RTK-GPS uses differential-GPS with carrier phase ambiguity resolution to achieve horizontal accuracies of <1 cm and vertical accuracies from 2 – 10 cm (CMT Z33 Operator’s Manual, 1997). A simple kriging procedure within ArcGIS was used to interpolate the elevation points to a 5m grid resolution. Elevation and slope are shown for both land uses in Figure 2. Samples were grouped by core horizons and diagnostic class (epipedon and subsoil) for most analyses.

Geostatistical analysis was done using the Geostatistical Analyst extension of ArcGIS. Various techniques were attempted to fit semi-variograms models to the soil properties at each grid point (Johnston et al, 2001). Given the relatively small area being considered, we
considered all soil properties to have second-order stationarity (Webster, 2000). Secondary attribute maps of soil map units, landscape positions, and elevation classes were used to attempt to improve prediction values (Goovaerts, 1999; Odeh et al., 1994). The parameters of these models were used to evaluate and compare the spatial variability of each property in the prairie and the field. These semi-variogram functions were then used with ordinary kriging to predict property values on a grid across each land use.

Geostatistical tools were used to model and predict soil properties within each land use individually. Three different data sets were used: all described cores, laboratory analyzed cores, and selected texture cores. Epipedon thickness, surface sample bulk density, elevation and slope were analyzed for all described cores. Laboratory analyzed cores were used to determine particle size distribution, SOC, pH, and WSA. These measurements, with the exception of particle size distribution, were averaged over the epipedon and subsoil of each core to provide a basis for comparisons between and within land uses. The particle size distribution of laboratory analyzed cores was done on surface horizons only. Epipedon thickness, bulk density, elevation, and slope were also analyzed in just these laboratory cores to provide information about bias due to the location of the selected nested grid. A selected set of cores, sixteen in each land use, were chosen for particle size analysis on all horizons.

Several techniques were used in an attempt to obtain the best model fit and prediction accuracy for each property. Best fit was measured by visual and statistical fitting techniques recommended by Webster and Oliver (2001) and minimizing cross-validation root mean square prediction error of ordinary kriging (RMSE) (Johnston et al., 2001; Lark, 2000). Models were first fit using the geostatistical wizard default values for a spherical semi-variogram. Other models (e.g. circular, exponential) were attempted and rejected when they
did not improve visual fit. Then each property model was evaluated for trend and anisotropy. Trends were not apparent along any consistent directional axis. Detrending the values did not measurably improve the model fit or accuracy for any property. While anisotropy was visually evident in some properties, such as agriculture field epipedon thickness, accounting for it in the model actually increased the RMSE. Since land use and soil series classes account for some of soil variability (Chap 2.), they were used to try and improve prediction accuracy through the use of class residuals (Goovaerts, 1999; Odeh et al., 1994). Each individual measurement was subtracted from the mean in which the class fell, creating a soil series and landscape position residual for each property. When these residuals are modeled the semi-variograms have similar nugget to sill ratios and RMSE to the original data models. Therefore, the data presented are for the default model given by the Geostatistical Wizard package in ArcGIS.

**Results and Discussion**

A summary of the spherical semi-variogram model parameters for epipedon properties is given in Table 1. A separate analysis was done for all described and laboratory cores. The nugget:sill ratio indicates the degree of spatial dependence and variability for the property being modeled (Isaaks and Srivastava, 1989; Knighton and Wagenet, 1987). Values near zero indicate strong spatial dependence of measurements within the range. Values near 1 indicate that variance is due to measurement variability and that spatial relatedness is limited. The root mean square prediction error (RMSE) is used to evaluate the prediction accuracy of each model. Root mean square prediction error is calculated from the residuals of actual and predicted values using a procedure known as cross-validation (Johnson et al., 2001). Range is indicative of the uniformity of the property in question. Long ranges
indicate more uniform properties. The range value of 593.7m is prevalent across properties and land uses (Table 7 and 8). These values are related to the starting values that Geostatistical Wizard begins it iterations with when fitting a semi-variogram model. They are based on an algorithm that uses the maximum distance between points and hence are the same for each model in this study (Johnston et al., 2001).

The parameters for the semi-variogram models of all description cores, including the properties of epipedon thickness, bulk density, elevation and slope, are given in Table 1. Epipedon thicknesses have very different models for each land use. The lower nugget:sill ratio of the agricultural field indicates that there is greater spatial dependence in that model. The larger nugget:sill ratio of the prairie indicates that epipedon thickness is not spatially dependent within the range of sampled locations. There is as much variation in epipedon thickness of cores taken near one another as in cores taken farther apart.

The model parameters of bulk density are similar for each land use. The nugget:sill ratio indicates that there is little or no autocorrelation in bulk density. This corroborates the findings of the GIS analysis (Chap. 2) that the variation is controlled by variable, discrete, finel scale perturbations and not by landscape variables. While there may be spatiality to their disturbances, variable compaction and expansion of surface materials caused by tillage and biologic activity obscure any larger trends in bulk density across the landscape (Figure 4).

Slope and elevation vary continuously across the landscape, therefore they have a high degree of spatial dependence. The nugget:sill ratio are 0.0 for elevation and only slightly higher (ag 0.3, pr 0.1) for slope. The shorter lags and ranges for slope reflect the nature of the landscape with autocorrelation over smaller portions of the landscape. Low
slope areas occur at high and low elevations and greater slopes in between. Thus slope values are similar at short and long distances, with the greatest differences in slope occurring in the middle range of distances sampled.

Soil organic carbon contents on both a weight by weight and weight by volume (Figure 3) basis have different distributions in each land use. SOC content in the agricultural field has spatial dependence in both (n:s = 0.3, 0.5, respectively) while the prairie has none in either (n:s = 1.0, 26.7, respectively). The nugget:sill ratio of 26.7 in the prairie reflects the counter-intuitive distribution of SOC by volume in the prairie (Chapter 2). There are greater differences at shorter distances than there are at longer ones (Figure 3). To further illustrate this point, the variance of SOC within the nested grid (0.70) is the same as the variance across the entire sample area (0.70). Bergstrom et al, 2001 found that organic carbon mass was spatially dependent across two tillage systems in Chernozomic soils in Canada. Cultivation has also been shown to increase the range (or maximum distance of spatial dependence) for SOC and other properties (Cambardella et al., 1994; Robertson et al., 1993). In this study, the agriculture field had a shorter range in the weight by weight model and an equal range in the weight by volume model. However, the lack of spatial dependence in the prairie makes the comparison of range values dubious.

The prairie and agricultural field have similar models for pH and % WSA content. Both the prairie and agricultural field samples have little spatial dependence, or autocorrelation, in pH. The n:s ratio is only slightly below one (ag 0.9, pr 0.6) and the ranges are similar (ag 246.7m, pr .304.6m) for each. Water stable aggregate content has no autocorrelation for either land use with n:s ratios of 3.2 in the agricultural field and 1.6 in the prairie. The prairie does have a shorter range (222.0 m) than the agricultural field (592.7m).
Water stable aggregate content may be controlled by the same type of discrete, fine scale factors (such as tillage and biota disruptions) that influence bulk density and make it difficult to model with autocorrelation, or distance, alone.

Modeling of epipedon thickness, bulk density, elevation, and slope with only those data points that were selected for laboratory analyses changes some of the model parameters. The nugget:sill ratio of the selected sample set is lower for prairie epipedon thickness, but greater for the agricultural model. The range is shorter for epipedon thickness in the field but not in the prairie. For bulk density, the same pattern holds but the increase in n:s ratio is even greater. The RMSE of predicted bulk density is also lower than the model with all described cores. Reducing the number of samples analyzed has reduced the range of bulk densities represented from $0.61 - 1.75 \text{ g cm}^{-3}$ to $0.72 - 1.34 \text{ g cm}^{-3}$ in the prairie and $0.72 - 2.03 \text{ g cm}^{-3}$ to $0.94 - 1.84 \text{ g cm}^{-3}$ in the agricultural field. This allows the model to do a better job of smoothing the trend across the prairie, but not the agricultural field. With fewer measurements to be binned into each lag class, local variation does not cancel out the autocorrelation causing a greater change in the semi-variogram at short distances for laboratory analyzed cores. There is not a great change in the model parameters of elevation when only the selected sample set is used. The prairie has an increase in n:s ratio of the slope model when using only the lab analyses samples. Reducing the sample size causes both the elevation and slope RMSE to be increased.

The particle size analyses of surface horizons show a great degree of autocorrelation for almost all fractions in both land uses (Table 2). There is no consistent trend between land uses in n:s ratio, range, or RMSE across particle size fractions. All nugget:sill ratios are less than 0.51 except for coarse silt and very fine sand (fraction b) in the prairie. The nugget is
zero for very coarse sand, medium sand, and fine sand for both land uses, and coarse sand and very fine sand (fraction a) in the prairie. The agriculture field has a shorter range for very coarse sand, coarse sand, medium sand, and coarse silt while the prairie has shorter ranges for fine sand, very fine sands (fractions a & b), fine silt total silt and total clay. RMSE is similar between land uses for any given particle size fraction. The sum results of these statistics indicate that the spatial distribution of particle size fractions is similar for each land use differing only in the range of their spatial dependence.

The number of cores analyzed in their entirety for particle size distribution (16) is not great enough for a robust geostatistical analysis. However, information can still be gleaned from the differing patterns of surface horizon, epipedon, and subsoil textures (Figure 5). When the average particle size fractions of epipedons are analyzed the results are similar to the analyses of the 63 surface horizon samples with a few important differences. The agricultural field has a greater nugget:sill ratio for all fractions except fine sand (where the prairie has a greater ratio) and fine silt and clay (where the ratios are the same). Visual analysis of ordinary kriged prediction maps indicates that the general trends of particle size distribution are generally the same for the surface horizons and epipedons overall. Nuggets are also very small or zero when modeling the semi-variograms of subsoil fractions. The n:s ratios, ranges and RMSE are once again very similar for both land uses.

**Conclusions**

Standard spherical semi-variogram models were found to do the best job of modeling soil properties in both the agricultural field and the prairie. These fitted models indicate that the agricultural field has greater spatial dependence, as measured by nugget:sill ratio, than the prairie. SOC measurements were found to be spatially dependent in the agriculture field
but not in the prairie. Nearly all particle size fractions were spatially dependent for both land uses. This indicates that the spatiality of SOC has been influenced by land use while particle size distribution has not.

The conclusions drawn about epipedon thickness and bulk density depended on the set of cores chosen for modeling. In the full description set, epipedon thickness was found to be spatially dependent in the agriculture field, but not in the prairie while bulk density was spatially dependent for neither. In the subset of laboratory analyzed cores, epipedon thickness was not spatially dependent for either while bulk density was spatially dependent in the prairie. By selecting one nested grid, concentrated in a small area, for laboratory analysis, we may be biasing the analysis of these properties. In contrast, the selection of a fewer number of widely dispersed locations for full core particle size analysis did not change any of the conclusions drawn. For future studies, the selection of nested grids should be partitioned across the landscape using topographic variables or expert information systems.

References


Table 1. Summary of spherical semi-variogram model parameters of ordinary kriging for epipedon properties.

<table>
<thead>
<tr>
<th></th>
<th>Lag (m)</th>
<th>Nugget</th>
<th>Sill</th>
<th>N:S †</th>
<th>Range (m)</th>
<th>RMSE</th>
</tr>
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<tr>
<td><strong>All Cores</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td><strong>Thickness ‡ cm</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
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</tr>
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<td><strong>Thickness ‡ cm</strong></td>
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</table>

† Ag, agricultural field; Pr, prairie; SOC, soil organic carbon; WSA, water stable aggregate content; N:S, nugget:sill ratio; RMSE, root mean square prediction error, SOC, soil organic carbon; WSA, water stable aggregate content
‡ Thickness refers to thickness of the epipedon determined in this case by the presence of mollic colors (Soil Taxonomy, 1999).
Table 2. Summary of spherical semi-variogram model parameters of ordinary kriging for surface horizon particle size distribution fractions.

<table>
<thead>
<tr>
<th>Fraction (mm)</th>
<th>Lag</th>
<th>Nugget</th>
<th>Sill</th>
<th>N:S†</th>
<th>Range</th>
<th>RSME</th>
</tr>
</thead>
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<tr>
<td>Very coarse sand (2.0 - 1.0)</td>
<td>Ag 50.0 0.00 0.12 0.00 108.24 0.34</td>
<td>Pr 50.0 0.00 0.92 0.00 330.73 1.01</td>
<td></td>
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<tr>
<td>Coarse sand (1.0 - 0.5)</td>
<td>Ag 15.1 0.23 0.79 0.29 92.175 1.01</td>
<td>Pr 50.0 0.00 3.10 0.00 347.79 1.59</td>
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<td>Medium sand (0.5 - 0.25)</td>
<td>Ag 20.3 0.00 5.18 0.00 130.34 2.05</td>
<td>Pr 50.0 0.00 8.08 0.00 444.04 2.28</td>
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<tr>
<td>Fine sand (0.25 - 0.125)</td>
<td>Ag 50.0 0.00 33.12 0.00 592.66 4.72</td>
<td>Pr 50.0 0.00 2.79 0.00 348.88 1.46</td>
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<td>Very fine sand a (0.125 - 0.063)</td>
<td>Ag 50.0 0.33 1.01 0.33 592.66 0.91</td>
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<td></td>
<td></td>
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</tr>
<tr>
<td>Very fine sand b (0.063 - 0.053)</td>
<td>Ag 50.0 0.06 0.00 0.00 567.58 0.22</td>
<td>Pr 18.3 0.01 0.01 0.51 110.58 0.13</td>
<td></td>
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</tr>
<tr>
<td>Total Sand (2.0 - 0.053)</td>
<td>Ag 50.0 0.89 111.14 0.01 592.66 7.03</td>
<td>Pr 50.0 1.28 49.83 0.03 503.8 5.64</td>
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<tr>
<td>Coarse Silt (0.053 - 0.020)</td>
<td>Ag 16.5 5.73 7.25 0.79 106.08 3.29</td>
<td>Pr 50.0 9.63 7.68 1.25 592.66 3.46</td>
<td></td>
<td></td>
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</tr>
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<td>Fine Silt (0.020 - 0.002)</td>
<td>Ag 50.0 4.28 11.32 0.38 592.66 3.29</td>
<td>Pr 13.7 4.62 8.98 0.51 162.73 3.25</td>
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<td></td>
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<tr>
<td>Total Silt (0.053 - 0.002)</td>
<td>Ag 50.0 10.76 31.74 0.34 592.66 5.03</td>
<td>Pr 34.6 0.00 33.45 0.00 181.24 5.20</td>
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<tr>
<td>Total Clay (&lt;0.002)</td>
<td>Ag 50.0 1.96 15.71 0.12 592.66 2.84</td>
<td>Pr 50.0 2.54 6.50 0.39 299.49 2.51</td>
<td></td>
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</tbody>
</table>

† Ag, agricultural field; Pr, prairie; N:S, nugget:sill ratio; RMSE, root mean square prediction error
Figure 1. Location of study site on the Iowan Surface in northeastern Iowa. Locations are shown for all described cores, laboratory analyzed cores, and selected texture cores.

Figure 2. Digital elevation model and slope derived from RTK-GPS data using ArcGIS GIS for the agriculture field (AG) and the prairie (PR).
Figure 3. Semi-variogram clouds of soil organic carbon (SOC) content by weight (g kg\(^{-1}\)) and volume (kg m\(^{-3}\)) in the a) agricultural field and b) prairie.
Figure 4. Ordinary kriging predictions using the semi-variogram models of the agriculture field (AG) and prairie (PR) for epipedon thickness, bulk density and soil organic carbon.
Figure 5. Predictions of clay content in surface horizons (63 sample points), epipedons, and subsoils (16 sample points) across the agricultural field (AG) and prairie (PR) using ordinary kriging.
CHAPTER 4. EVALUATING GIS AND GEOSTATISTICAL TECHNIQUES FOR DETERMINING THE SPATIAL DISTRIBUTION OF SOIL PROPERTIES

A paper to be submitted to Soil Science Society of America Journal

S.A. Wills, C.L. Burras, and J.A. Sandor

Abstract

While the effect of cultivation on soil properties has been well documented, its effect on the spatial distribution of soil properties is less well understood. The purpose of this study is to use GIS classes of soil series and landscape positions and geostatistics to characterize the spatial distribution of soil properties in a native prairie and agriculture field. Each land use was sampled on an unbalanced hierarchical nested grid for a total of 203 cores. All cores were described with standard nomenclature, 63 cores in each land use were analyzed for soil organic carbon (SOC), bulk density, water stable aggregates (WSA), pH, and surface horizon particle size distribution. The analysis of GIS classes indicated that epipedon thickness is spatially stratified within each land use. The analyses of SOC spatial dependence yielded mixed results depending on the method used. While soil series property means are significantly different in the prairie, geostatistical analysis shows that soil organic carbon is spatially dependent only in the agricultural field. Bulk density, pH, and WSA are not spatially dependent using any technique. GIS class analyses show no consistent trend in particle size distribution between fractions, classes, and land uses, but geostatistical analysis indicate that most fractions are spatially dependent in both land uses. While GIS and geostatistical analysis sometimes lead to different conclusions about the spatial distribution
of soil properties, they have nearly identical average predictions and prediction errors for all
properties.

**Introduction**

The impact of human land use on soils is profound. These impacts are apparent on
regional and local scales. In Iowa, more than 90% of the land has been extensively
cultivated, drained, fertilized and/or converted to vegetation much different than would
naturally exist (Whitney, 1994; Thompson, 1992). Soil researchers have long recognized the
impact of cultivation on soil properties. Jenny (1941) stressed the importance of human
impact on the five state factors of soil formation: climate, organisms, topography, parent
material and time. Subsequent authors have proposed ways to express human impacts on
soil through qualitative methods (Sandor et al, 2005; Amundson and Jenny, 1991; Yaalon
and Yaron, 1966; Bidwell and Hole, 1964). More quantitatively, numerous studies have
outlined the changes cultivation causes in individual soil properties. Cultivation influences
epipedon thickness because of differences in bioturbation, compaction, erosion, or deposition
(Buol et al., 2003; Hole, 1981). Cultivation has been shown to increase bulk density (e.g.
Cihacek and Ulmer, 1986; Coote and Ramsey, 1983), decrease soil carbon content (e.g.
Fenton et al., 1999) and disrupt soil structure (e.g. Kay, 1995; Perfect et al., 1990) through
mechanical action and decreasing root and microbial biomass (Stahl et al., 1999; Harris et al.,

Despite this robust historical data set, the majority of these studies lack a spatial
component. The effect of cultivation on the spatial distribution of soil properties is not well
understood. While the literature is replete with examples of land use comparisons, there are
fewer that systematically examine any differences in the distribution of those properties. The
primary focus of this study is to determine the influence of land use on the distribution of soil properties under an agriculture field and native prairie, on the Iowa Surface in northeast Iowa.

Soil maps provide a readily available source of soil property information that can be used to both stratify and extrapolate soil properties across landscapes and regions (Bouma et al., 1999; Burke et al., 1989; Voltz and Webster, 1990). Every soil map represents information that is simplified and organized based on the mapmaker’s underlying understanding of soil and its distribution across the landscape. In the United States, soil map units are grouped based on the underlying principles of Soil Taxonomy (Soil Survey Staff, 1999). Landscapes can also be divided into elements, or landscape positions, that can be studied and compared (Ventura and Irvin, 2000; Daniels and Hammer, 1992; Bloom, 1991; Conacher and Dalyrmple, 1977; Ruhe, 1975;). In this study, we use previously delineated soil series map unit boundaries (Iowa Cooperative Soil Survey, 2003) and manually digitized landscape position maps to evaluate spatial distribution of soil properties across each land use.

In these GIS techniques, soil properties are delineated as class polygons. The size of these polygons is limited by the scale of final map productions (Zhu, 2001). New computer applications have allowed wide-spread development and use of more detailed analytical and predictions techniques such as geostatistics. Geostatistics can be used to analyze any feature that exhibits spatial dependence (Webster and Oliver, 2001; Journel and Huijbrechts, 1978; Matheron, 1963). They provide a statistically robust technique for analyzing the spatial distribution of soil properties at various locations and conditions. Cultivation has been shown to decrease the variability of SOC, soil organic carbon (Cattle, 1994). Using
geostatics, more specific statements can be made about the changes in spatial distributions of soil properties. Cultivation has been shown to increase the maximum distance of spatial dependence for SOC and other properties (Cambardella et al., 1994; Robertson et al., 1993). Paz-González et al. (2000) found that cultivated soils were more homogeneous than soils under natural vegetation, with increased small scale continuity (reduced nugget effects) of organic matter and cation exchange capacity.

Addressing the uncertainty in spatial predictions has grown in importance as minimally disturbed soils become increasingly rare. Pedological insights into human impacts are crucial to developing environmentally benign yet economically sustainable soil management practices (Lal and Stewart, 1995). We will evaluate the ability of soil series map units, landscape positions, and geostatistical models to describe the spatiality of each land use.

**Materials and Methods**

**Study Area**

The study sites are on the Hayden Prairie State Preserve and an adjacent agricultural field in northeast Iowa (Figure 1). Most of the soils in this area are formed in one to two meters of Iowan Surface pedisediment, which overlies a thick, dense Pre-Illinoian glacial till (Ruhe, 1969; Prior, 1991). Tallgrass prairie was the native vegetation for the past 8,000 to 9,000 years (Thompson, 1992). Soils formed from this combination of the Iowan Surface deposits and tallgrass prairie are extensive in Iowa and southeastern Minnesota, with more than 80% of the area currently dedicated to row crop production (Iowa Department of Natural Resources, 2000). Hayden Prairie is perhaps the only remaining large prairie
remnant on the Iowa Surface while the cropped field represents the area's predominant land use. The prairie and field provide an ideal contrast to evaluate the effects of a centuries worth of agricultural cultivation on soil property distribution.

**Sampling**

Each land use was sampled in an unbalanced hierarchical nested grid. This was done to determine the scale of spatial dependence and improve sampling efficiency (Borgelt et al., 1997; Oliver and Webster, 1986). A square grid was created and georeferenced to minimize the number of samples while assuring a range of spatial scales. A 24 ha area of both the prairie and agricultural field was divided into a 100m grid. This grid was separated into 6 blocks. Within each block, one 100m square was randomly selected for further division into a nested grid. Each nested grid was composed of grid points that were 50, 25, 12.5, 5, and 2.5m apart (Figure 1). Cores (0.05m x 1.5m) were taken at each grid node with a truck mounted Giddings hydraulic soil probe. There were a total of 203 cores taken in each land use. Sixty-three of those cores were analyzed for soil organic carbon (SOC) content, pH, water stable aggregate content (WSA).

**Field Description**

All 406 sampled cores were described and analyzed for bulk density. Field descriptions were done using standard techniques and nomenclature (Schoenberger et al., 2002). Bulk density was measured on horizons and predetermined depth increments of 0-5, 5-10, 15-30, 30-50, and 50-100cm for each core. A portion of each horizon and depth increment was cut, weighed, and oven dried to determine bulk density by a modified volumetric core method (Konen, 1999; Soil Survey Staff, 1996).
Laboratory Analysis

Laboratory analyses were done on the samples from 100m grid cores and one randomly selected nested grid from each land use (63 cores from each land use). These cores will be referred to from this point on as laboratory cores. These analyses included pH, soil organic carbon, chroma meter color, water stable aggregate content, and surface horizon texture (Soil Survey Staff, 1996). A subset of these cores, chosen to represent all landscape positions, was also analyzed for particle size distribution for all horizons. Samples were divided by horizon and depth increment for each core analyzed. Samples were ground to pass a 2mm sieve for further analysis. Chroma Meter color was used to determine Munsell hue, value and chroma for moist and dry ground samples (Konen et al., 2003). Percent water stable aggregate (WSA) content was determined on samples of depth increments 0-5, 5-10, and 15 cm to the bottom of the epipedon. Aggregates having 0.5 - 1 mm diameters were wet and sieved as outlined by the Soil Survey Staff (1996). The average of those measurements was considered to be % WSA content for the epipedon. Soil pH was determined on a 2:1 soil paste with 5 g of soil (Soil Survey Staff, 1996) for each horizon and depth increment. Soil particle size distribution was determined using the volumetric pipette procedure (Soil Survey Staff, 1996). Soil organic carbon was determined by the Iowa State Soil Testing Laboratory. Total organic carbon was measured with a Leco LC2000 (Model CHN 600, LECO, St. Joseph, MI). Samples with pH >7.5 were analyzed by acid injection (Sherrod et al., 2002) to determine inorganic carbon content. That value was subtracted from total carbon to arrive at the SOC values.
**Statistical Analysis**

Cores were grouped by land use, soil series, and landscape position with the GIS software ArcGIS (ESRI Redlands, CA) (Figure 2). Soil series polygons were obtained from the Iowa Cooperative Soil Survey (ICSS, 2003). Landscape positions were identified at sample locations in the field using the summit, shoulder, backslope, footslope and toeslope model (Ruhe, 1975). GIS polygons were manually digitized using field classification, slope and curvature derived from the DEMs using ArcGIS. Digital elevation models (DEM) were developed from elevation data collected with vehicle based real time kinematic global position system (RTK-GPS) in each land use. RTK-GPS uses differential-GPS with carrier phase ambiguity resolution to achieve horizontal accuracies of <1 cm and vertical accuracies from 2 – 10 cm (CMT Z33 Operator’s Manual, 1997). A simple kriging procedure within ArcGIS was used to interpolate the elevation points to a 5m grid resolution. Soil series, landscape positions, elevation, and slope are shown for both land uses in Figure 2. Samples were grouped by core horizons and diagnostic class (epipedon and subsoil) for most analyses. All horizons with Munsell value and chroma < 3 were considered part of the epipedon and all horizons below the epipedon were considered part of the subsoil. Standard descriptive statistics, including means and standard errors, were used to evaluate each class using SAS 9.1 for Windows (SAS Institute Inc., Cary, NC). Analysis of variance (ANOVA) was done to determine the ability of grouping schemes to explain soil property variance between soil series, landscape positions, and land use. Significance was considered at the 0.05 level. Significant property models within each land use were considered an indication spatial stratification of that property across the landscape.
Geostatistical analyses were done using the Geostatistical Analyst extension of ArcGIS. Various techniques were attempted to fit semi-variograms models to the soil properties at each grid point (Johnston et al, 2001). Secondary attribute maps of soil map units, landscape positions, and elevation classes were used to attempt to improve predict prediction values (Goovaerts, 1999; Odeh et al., 1994). The parameters of these models were used to evaluate and compare the spatial variability of each property in the prairie and the field. These semi-variogram functions were then used with ordinary kriging to predict property values on a grid across each land use.

Finally, predictions using GIS and geostatistics mapping were compared by prediction accuracy and land use averages. The accuracy of the model indicates the explanatory usefulness of each model for each property and land use. Root mean square prediction error (RMSE) was used to evaluate the accuracy of each prediction technique. This was done through ANOVA (SAS) for GIS classes and cross-validation (Geostatistical Analyst) in geostatistics. This represents a summed deviation of each measurement from the predicted average at that location. Average property prediction was done by taking area weighted property means of each land use for each prediction strategy. For GIS analyses, the mean of each class was weighted by the area of that class. For geostatistical analysis, raster calculations take the value of each cell and cell size to produce a weighted average. (Voltz and Webster, 1990).

The spatial distributions of soil properties were previously determined by GIS (Chapter 2) and geostatistics (Chapter 3) techniques. Three different data sets were analyzed: all described cores, laboratory analyzed cores, and selected texture cores. Epipedon thickness, surface sample bulk density, elevation and slope were determined for all
described cores. Laboratory cores were analyzed for particle size distribution, SOC, pH, and WSA. These measurements, with the exception of particle size distribution, were averaged over the epipedon and subsoil of each core to provide a basis for comparisons between and within land uses. The particle size distribution of laboratory analyzed cores was done on surface horizons only. A selected set of cores, sixteen in each land use, were chosen for particle size analysis on all horizons.

For GIS class models, soil series and landscape positions, analysis of variance (ANOVA) was done to access the efficacy of each model in capturing the variance of each property across. If the distribution of soil properties across the landscape was completely random, GIS model classes would not be significantly different from one another. Conversely, those model classes that are significantly different from one another within each land use can be considered to represent spatially dependent properties.

Geostatistical tools were used to model and predict soil properties within each land use individually. Models were fit using the ArcGIS Geostatistical Wizard default values for a spherical semi-variogram. The nugget:sill ratio was used to indicate the degree of spatial dependence and variability for the property being modeled (Isaaks and Srivastava. 1989; Knighton, and Wagenet. 1987). Values near zero indicate that the spatial dependence of measurements within the range is strong. Values near 1 indicate that variance is due to measurement variability and that spatial relatedness is limited. For both GIS and geostatistical analysis, the root mean square prediction error (RMSE) is used to evaluate the prediction efficiency of each model. Root mean square prediction error was calculated from the residuals of actual and predicted values. Lower RMSE indicate a better model fit.
One of the primary advantages of using GIS and geostatistics to evaluate spatial distribution is that they can both be used to visually represent soil properties in space. Furthermore, those maps provide the basis for further spatial analysis. The predictions from ordinary kriging and the polygon GIS layers of soil series and landscape position were used to average and sum soil properties over the area of interest (Tables 1, 2, and 3). This provides a measure of the differences caused by using soil property measurement and prediction schemes.

**Results and Discussion**

Examining epipedon thickness as grouped and predicted with soil series map units, landscape positions, and ordinary kriging provides useful insights (Figure 3). Soil series and landscape positions were significantly different between and within each land use. In contrast, the semi-variogram model of epipedon thickness indicated spatial dependence in the agricultural field but not in the prairie. When the prediction maps are reviewed, landscape positions are so large as to obscure the small area of greatest epipedon thickness in the prairie, however, the thinnest areas in agriculture field are shown in finer detail. Ordinary kriging gives increased detail in property distribution but could also be skewed by outlying data points or measurement errors (especially in areas with wide sample spacing). Despite the model differences, ordinary kriging does as good of job predicting epipedon thickness, as indicated by RMSE, in the prairie as it does in the agricultural field. Comparing the ordinary kriging predictions with the landscape position and soil series maps helped identify the reason for the higher agricultural epipedon values for the Clyde soil series and footslope epipedons (Chap. 2).
In contrast to epipedon thickness, bulk density was not shown to be spatially dependent by soil map units, landscape positions, or geostatistics. Epipedon thickness generally varies gradually over the landscape in response to multiple factors. Bulk density appears to be controlled by discrete, locally variable factors such as tillage, compaction, and bioturbation (Figure 4). While there may be spatiality to their disturbances at fine scales, these activities obscure any larger trends in bulk density across the landscape.

Soil organic carbon content maps show a different distribution than epipedon thickness (Figures 5, and 6). Soil organic carbon content was significantly different for soil series in the prairie but not in the agricultural field. Landscape positions were not significantly different within either land use although individual landscape positions had an average of 10 g kg$^{-1}$ greater SOC contents in the prairie than in the agriculture field. The agricultural samples exhibited strong spatial dependence with a short range of influence in geostatistical modeling. This influence is so strong that the SOC by weight prediction map is dimpled around individual measurements (Figure 5). These extreme model parameters and dimpled prediction map are not evident in SOC contents on a weight by volume basis (Table 1 and Figure 6). In contrast, prairie SOC content is most variable at short distances for both weight by weight and weight by volume measurements, indicated by a high nugget:sill ratio 26.7, (Chapter 3, Table 1). This prediction map of SOC in the prairie has some striping around the nested grid, but overall represents a smooth, continuous distribution.

The distribution of SOC in ordinary kriging prediction maps are much better correlated to the soil map units than landscape positions. The large size of footslope polygons obscures the areas of highest values while summits overestimate the extent of their low values. In contrast, the low and high of the soil series map units encompass relatively
homogenous areas (Figures 5 and 6). Despite these differences the weighted average and RMSE predicted across each land use is nearly identical for each prediction strategy.

Each mapping strategy highlights the different distributions of SOC across the landscape in each land use. In the agricultural field, the highest SOC values are associated with the lowest elevations while the highest prairie SOC values occur at mid-elevations. While this may be partially due to sampling bias, as discussed previously, there are pedological explanations as well. There are indications that the hydrology of these soils is such that SOC decomposition would be inhibited. We noted wetness and standing water in these areas at the time of sampling. The presence of hydrophilic plants (blue flags, marsh marigolds, young swamp milkweed, and sedges: *Iris virginica*, *Caltha palustris*, *Asclepias incarnate*, and *Carex sp*) indicates that this area is waterlogged some significant portion of the year (Thompson, 1992; Bishop and Van der Valk, 1982). The elevation and slope maps indicate that this may be the head of an ephemeral drainageway (Figure 2). Thompson et al. (1998) found that a similar landscape in Minnesota had evidence of lateral flow along low relief drainage ways. Furthermore, the dense till with depth may be restricting downward flow and acting as an aquitard. The average bulk densities of the epipedons of the agricultural field and prairie are 1.38 g cm\(^{-3}\) and 1.05 g cm\(^{-3}\), respectively while the subsoils are 1.71 g cm\(^{-3}\) and 1.80 g cm\(^{-3}\), respectively. In central Iowa, Steindwand and Fenton (1995) found that dense till retarded water movement downward and caused lateral flow. The lateral flow may be collecting in these mid-elevation areas. The highest SOC regions in the prairie are mapped as poorly drained Clyde (Typic Endoquoll) and Jameston (Typic Argiaquoll) poorly drained and somewhat poorly drained Protovin (Aquic Argiudoll). These are consistent with the conditions in the prairie, however, these soils are also mapped in the...
agriculture field where these conditions are no longer present. While the features used to
define these soil series, gleyed subsoil etc., are still present at mid-elevations in the
agricultural field, these are most likely relict features that do not reflect the current moisture
regime under artificial drainage (James and Fenton, 1993). Agricultural drainage has
changed soil conditions such that SOC contents are equivalent between soil series.

Surface horizon particle size distribution prediction maps are vastly different between
prediction strategies. Neither the soil series maps nor the landscape position maps convey
the distributions apparent in the ordinary kriged map (Figures 7 and 8). The soil series and
landscape positions are disjointed across both the land uses. Graphical representation
highlights the differing rank of classes in each land use. For instance, the Clyde series has
the second highest sand content in the agriculture field but the lowest in prairie. This
mapping technique, with color assigned by class and not relative property value highlights
small differences that may not be pedologically important (Figure 7). An alternative method
of mapping could be used to display only those differences that are most relevant.

Converting GIS class polygons to a raster prediction grid (with values from soil series
and landscape positions predicted on the same square grid as the ordinary kriged predictions)
and stretching the predicted values from high to low values creates a map that shows
differences in color relative to the differences in prediction value (Figure 9). The raster maps
highlight the greater variation between soil series surface horizon clay content in the prairie.
In the agricultural field, a few soil series have similar clay content with only one being
considerably different than the others.

The ordinary kriging predictions of both clay and sand in the surface horizon (Figure
7 and 8) show a continuous surface of clay content across both land uses. Stretching the
color representation of the raster maps creates greater visual continuity between land uses in soil series and landscape position predictions than the original class maps, but still appears less continuous than the ordinary kriged prediction grid. This continuity is also apparent for ordinary kriging of epipedon and subsoil average particle size classes that used only 16 cores each to model and predict their values (Figure 10). This indicates that while land use classes may have different particle size distributions in some cases, those differences are related more to the extent and location of those classes in each land use and not an effect of land use itself.

There is further evidence that land use has not altered the distribution of particle size fractions. When average predictions and their error are compared, once again there is very little difference in either between prediction schemes for surface horizons. Epipedon and subsoil weighted averages are more variable, with a maximum range of 6% for any one size fraction vs. 3.1% for surface horizons, and their RMSE’s are larger than the surface horizon predictions. This is remarkable given the great reductions in sample size (63 surface horizons, 16 epipedons and subsoils). The importance of this increased variability and RMSE depends upon the intended use of the data.

**Summary**

The native prairie and agriculture field differed in the spatial distribution of epipedon thickness and SOC content. While epipedon thickness was significantly different for soil series map units and landscape positions within and between land uses, the semi-variogram model indicates that epipedon thickness is spatially dependent only in the agricultural field. Bulk density, pH, and WSA have significantly different averages for each land use, but no
class model has significant differences within each land use. These properties also show little to no spatial dependence through geostatistical analysis.

Soil organic carbon content analyses yield mixed results depending on the measurement (weight v. volume), class (soil series v. landscape position) and land use being considered. Soil series were significantly different in the prairie, but no other GIS model was significant for SOC contents within a land use. Soil organic carbon was shown to be spatially dependent with geostatistics in the agricultural field but not the prairie. When examining the distribution of organic matter and cation exchange capacity, Paz-González et al. (2000) found that while cultivated soils were more homogeneous, with increased small scale continuity (reducing nugget effects), natural vegetation had a pure nugget effect. Because SOC content is being controlled by localized, but repeating factors, its spatial distribution is not modeled well by simple autocorrelation. Soil series, which are mapped on the basis of the same factors controlling SOC content, delineate those differences well. In this case, lack of spatial dependence in the geostatistical model does not indicate a random distribution of SOC across this land use, but some combination of increased small scale variability and spatial dependence that cannot be adequately described given the constraints of our sampling scheme and spatial model. We argue that the lack of these patterns in the agriculture field is due, in part, to the homogenizing of the soil moisture regime in the agriculture field by means of tile drainage.

Averaged across each land use, particle size distribution in surface horizons was significantly different for some size fractions. GIS class analyses show no consistent trend between fractions, classes, and land uses. Individual classes are generally not different between land uses. Within land uses, classes are more often significant for particle size
fractions of soil series in the prairie than the agricultural field. While this may reflect the homogenization of agriculture soil properties through cultivation, we would expect this to also create differences in individual classes between land uses. Geostatistical analysis indicates that most fractions are spatially dependent in both land uses. Therefore, despite differences in average particle size fraction values, we conclude that these differences represent the different extent of soil series and sampling location in each land use and not differential removal or deposition across, off of, or onto either study area.

Visual inspection of the prediction maps can illustrate the interplay of sampling strategy and class boundaries with the property predictions across each landscape. The presence or absence of property continuity across the land use boundary may be difficult to quantify, but it can be easily illustrated on a map. The relative ranking of high and low values is continuous between land uses for epipedon thickness and bulk density. Soil organic carbon content and particle size distribution appear continuous for ordinary kriged predictions but less so for soil series and landscape positions. While they provide valuable information and fodder for future investigations, definitive conclusions cannot be made from these maps because they depend on the cartographic methods used to display the data.

A more quantitative comparison of each prediction scheme is given by weighted average and RMSE for each property. For epipedon thickness, there is little to no difference in either the weighted average or RMSE of prediction strategies. Soil organic carbon content averages are slightly more variable when considered on a weight per weight basis. pH, SOC (kg m⁻³), elevation, and slope have virtually no differences in weighted average or RMSE between models. Water stable aggregate content has slightly more variation in predicted weighted average, but it also had greater variance in the measurements themselves (as
measured by standard error). In all cases, the differences are within the range of the standard error for that property and land use. For the small differences that are apparent, there is no consistent trend between prediction schemes and land use.

**Conclusions**

GIS and geostatistics provide useful tools to evaluate the distribution of soil properties between and within these land uses. This study has shown that each technique can highlight some differences in distribution while minimizing other. Although many prediction strategies create conflicting conclusions about the distribution of soil properties, the sum total of the predictions is nearly identical. Therefore we conclude that these various schemes may be useful for detailed analysis of a few sites. Geostatistics improved the detail of our knowledge about this small area. However, the method of prediction may be less important when the purpose is to quantify properties over larger areas.

**References**


Table 1. Average epipedon values weighted by area using soil series map units, landscape positions, and ordinary kriging.

<table>
<thead>
<tr>
<th></th>
<th>Soil Series</th>
<th>Landscape Position</th>
<th>Ordinary Kriging</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Wt. Avg.</td>
<td>RMSE</td>
<td>Wt. Avg.</td>
</tr>
<tr>
<td>All Cores</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Thickness cm</td>
<td>Ag</td>
<td>37.8</td>
<td>12.71</td>
</tr>
<tr>
<td></td>
<td>Pr</td>
<td>41.7</td>
<td>10.82</td>
</tr>
<tr>
<td>Bulk Density g cm⁻³</td>
<td>Ag</td>
<td>1.24</td>
<td>0.26</td>
</tr>
<tr>
<td></td>
<td>Pr</td>
<td>1.14</td>
<td>0.22</td>
</tr>
<tr>
<td>Elevation m</td>
<td>Ag</td>
<td>390.2</td>
<td>1.53</td>
</tr>
<tr>
<td></td>
<td>Pr</td>
<td>372.2</td>
<td>2.89</td>
</tr>
<tr>
<td>Slope %</td>
<td>Ag</td>
<td>3.8</td>
<td>1.53</td>
</tr>
<tr>
<td></td>
<td>Pr</td>
<td>1.6</td>
<td>0.47</td>
</tr>
<tr>
<td>Laboratory Cores</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Thickness cm</td>
<td>Ag</td>
<td>35.3</td>
<td>11.78</td>
</tr>
<tr>
<td></td>
<td>Pr</td>
<td>43.8</td>
<td>10.01</td>
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<tr>
<td>Bulk Density g cm⁻³</td>
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<td>0.17</td>
</tr>
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<td></td>
<td>Pr</td>
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<td>0.10</td>
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<tr>
<td>SOC g kg⁻¹</td>
<td>Ag</td>
<td>20.52</td>
<td>5.33</td>
</tr>
<tr>
<td></td>
<td>Pr</td>
<td>32.87</td>
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<tr>
<td>SOC kg m⁻³</td>
<td>Ag</td>
<td>28.67</td>
<td>7.55</td>
</tr>
<tr>
<td></td>
<td>Pr</td>
<td>31.19</td>
<td>8.20</td>
</tr>
<tr>
<td>pH</td>
<td>Ag</td>
<td>5.9</td>
<td>0.47</td>
</tr>
<tr>
<td></td>
<td>Pr</td>
<td>5.2</td>
<td>0.40</td>
</tr>
<tr>
<td>WSA %</td>
<td>Ag</td>
<td>25.3</td>
<td>14.03</td>
</tr>
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<td></td>
<td>Pr</td>
<td>63.5</td>
<td>14.28</td>
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<td>Elevation m</td>
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<td>2.02</td>
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<td></td>
<td>Pr</td>
<td>394.0</td>
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<td>Ag</td>
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<td>1.13</td>
</tr>
<tr>
<td></td>
<td>Pr</td>
<td>1.6</td>
<td>0.48</td>
</tr>
</tbody>
</table>

† Ag, agricultural field; Pr, prairie; SOC, soil organic carbon; WSA, water stable aggregate content; N:S, nugget:sill ratio; RMSE, root mean square prediction error; Wt. avg., weighted average.

‡ Thickness refers to thickness of the epipedon determined in this case by the presence of mollic colors (Soil Taxonomy, 1999).
Table 2. Average particle size fractions of laboratory core surface horizons weighted by area using soil series map units, landscape position, and ordinary kriging.

<table>
<thead>
<tr>
<th>Fraction (mm)</th>
<th>Soil Series</th>
<th>Landscape Position</th>
<th>Ordinary Kriging</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Wt. Avg.</td>
<td>RMSE</td>
<td>Wt. Avg.</td>
</tr>
<tr>
<td>Very coarse sand</td>
<td>Ag</td>
<td>0.9</td>
<td>0.32</td>
</tr>
<tr>
<td>(2.0 - 1.0)</td>
<td>Pr</td>
<td>0.8</td>
<td>0.76</td>
</tr>
<tr>
<td>Coarse sand</td>
<td>Ag</td>
<td>4.0</td>
<td>0.93</td>
</tr>
<tr>
<td>(1.0 - 0.5)</td>
<td>Pr</td>
<td>3.5</td>
<td>1.34</td>
</tr>
<tr>
<td>Medium sand</td>
<td>Ag</td>
<td>9.8</td>
<td>2.23</td>
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<tr>
<td>(0.5 - 0.25)</td>
<td>Pr</td>
<td>8.8</td>
<td>1.82</td>
</tr>
<tr>
<td>Fine sand</td>
<td>Ag</td>
<td>7.4</td>
<td>4.86</td>
</tr>
<tr>
<td>(0.25 - 0.125)</td>
<td>Pr</td>
<td>6.1</td>
<td>1.21</td>
</tr>
<tr>
<td>Very fine sand a</td>
<td>Ag</td>
<td>3.3</td>
<td>0.95</td>
</tr>
<tr>
<td>(0.125 - 0.063)</td>
<td>Pr</td>
<td>2.8</td>
<td>0.54</td>
</tr>
<tr>
<td>Very fine sand b</td>
<td>Ag</td>
<td>0.8</td>
<td>0.23</td>
</tr>
<tr>
<td>(0.063 - 0.053)</td>
<td>Pr</td>
<td>0.7</td>
<td>0.12</td>
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<tr>
<td>Total Sand</td>
<td>Ag</td>
<td>26.2</td>
<td>7.79</td>
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<td>(2.0 - 0.053)</td>
<td>Pr</td>
<td>22.7</td>
<td>4.80</td>
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<tr>
<td>Coarse Silt</td>
<td>Ag</td>
<td>22.2</td>
<td>3.52</td>
</tr>
<tr>
<td>(0.053 - 0.020)</td>
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<td>25.5</td>
<td>3.25</td>
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<tr>
<td>Fine Silt</td>
<td>Ag</td>
<td>26.8</td>
<td>3.30</td>
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<tr>
<td>(0.020 - 0.002)</td>
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<td>3.14</td>
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<tr>
<td>Total Silt</td>
<td>Ag</td>
<td>48.0</td>
<td>5.48</td>
</tr>
<tr>
<td>(0.053 - 0.002)</td>
<td>Pr</td>
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<td>4.99</td>
</tr>
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<td>Total Clay</td>
<td>Ag</td>
<td>24.8</td>
<td>3.24</td>
</tr>
<tr>
<td>(&lt;0.002)</td>
<td>Pr</td>
<td>25.9</td>
<td>2.37</td>
</tr>
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</table>

† Wt. Avg, Weighted average; RMSE, root mean square prediction error; Ag, agriculture field; Pr, prairie.
Table 3. Average particle size fractions of selected core epipedon and subsoil horizons weighted by area using soil series map units, landscape positions, and ordinary kriging.

<table>
<thead>
<tr>
<th>Fraction (mm)</th>
<th>Soil Series</th>
<th>Landscape Position</th>
<th>Ordinary Kriging</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Wt. Avg†.</td>
<td>RMSE</td>
<td>Wt. Avg.</td>
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<tr>
<td>Epipedon</td>
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<tr>
<td>Total Sand</td>
<td>Ag</td>
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<tr>
<td></td>
<td>Pr</td>
<td>25.0</td>
<td>6.18</td>
</tr>
<tr>
<td>(2.0 - 0.053)</td>
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<tr>
<td>Total Silt</td>
<td>Ag</td>
<td>39.8</td>
<td>3.73</td>
</tr>
<tr>
<td></td>
<td>Pr</td>
<td>48.0</td>
<td>6.09</td>
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<tr>
<td>(0.053 – 0.002)</td>
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<td>Ag</td>
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<td>(&lt;0.002)</td>
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<td>Subsoil</td>
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<td>Total Sand</td>
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<td>7.94</td>
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<tr>
<td></td>
<td>Pr</td>
<td>41.6</td>
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<td>(2.0 - 0.053)</td>
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<tr>
<td>Total Silt</td>
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<td>27.3</td>
<td>6.97</td>
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<td></td>
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<tr>
<td>Total Clay</td>
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† Wt. Avg, Weighted average; RMSE, root mean square prediction error; Ag, agriculture field; Pr, prairie.
Figure 1. Location of study site on the Iowan Surface in northeastern Iowa, USA. Locations of all described cores, laboratory analyzed cores, and selected texture cores are shown on an aerial photograph.
Figure 2. Digital elevation model and slope position as derived from RTK-GPS data using ArcGIS overlain with soil series (Iowa Cooperative Soil Survey, 2003) and manually digitized landscape positions for the agriculture field, AG, and prairie, PR.
Figure 3. Epipedon thickness predicted across the agricultural field (AG) and prairie (PR) using soil map unit means, landscape position means and ordinary kriging.
Figure 4. Bulk density of all described cores for surface samples, predicted across the agricultural field (AG) and prairie (PR) using soil map unit means, landscape position means and ordinary kriging.
Figure 5. Epipedon soil organic carbon (SOC) content by weight, g kg\(^{-1}\), across the agricultural field (AG) and prairie (PR) using soil map unit means, landscape position means and ordinary kriging grid (5m) predictions.
Figure 6. Epipedon soil organic carbon (SOC) content by volume, g m$^{-3}$, across the agriculture field (AG) and prairie (PR) using soil amp unit means, landscape position means and ordinary kriging grid predictions.
Figure 7. Distribution of surface horizon clay content (%) across the agricultural field (AG) and prairie (PR) using soil map unit means, landscape position means and ordinary kriging grid (5m) predictions.
Figure 8. Distribution of surface horizon total sand content (%) across the agricultural field (AG) and prairie (PR) using soil map unit means, landscape position means and ordinary kriging grid (5m) predictions.
Figure 9. Display of surface horizon clay content (%) across the agriculture field (AG) and prairie (PR) using soil map unit means, landscape position means and ordinary kriging predicted on a regular square grid (5m) with color stretched from high to low values to highlight only meaningful differences.
Figure 10. Distribution of clay content in surface horizons (63 sample points), epipedons and subsoils (16 sample points) across the agriculture field and prairie using an ordinary kriging grid (5m) predictions.
CHAPTER 5. PREDICTION OF SOIL ORGANIC CARBON CONTENT USING FIELD AND LABORATORY MEASUREMENTS OF SOIL COLOR

A Paper to be submitted to Soil Science Society of America Journal

Skye A. Wills, C. Lee Burras, and Jonathan A. Sandor

Abstract

The understanding, prediction, and modeling efficiency of soil organic carbon (SOC) distribution across fields, watersheds, and larger regions requires a large number of samples that are costly to analyze. The purpose of this study is to evaluate soil color measurements to predict SOC for two land uses, agriculture and prairie. Munsell Soil Color Book (B) and chroma meter (C) color readings were taken at the mid-point depth of each horizon (HB, HC) and predetermined depth increments (IB, IC) on intact cores, split lengthwise. Horizon matrix (HD) colors were determined by standard description. Chroma meter was used to determine the color of prepared sample, ground to <2mm. These color measurements were used in a regression analysis to predict SOC content by weight (g kg\(^{-1}\)) and volume (kg m\(^{-3}\)). The best predictors for each technique are the full models which incorporate Munsell value and chroma along with the depth from which the measurement was taken. Separating samples by land use improved prediction of SOC. Transforming SOC content by log(10) improves the coefficient of determination for nearly all models. The best predictors of SOC were HD for SOC by weight (g kg\(^{-1}\)) (agriculture \(r^2 = 0.79\), prairie \(r^2 = 0.53\)), HB for SOC by volume (kg m\(^{-3}\)) (agriculture \(r^2 = 0.76\), prairie \(r^2 = 0.57\)), and IC and IB for log transformed SOC by weight and volume (agriculture \(r^2 = 0.84\), prairie \(r^2 = 0.62\)). This study indicates that SOC content predictions could be made with field measurements, by soil scientists using
traditional survey methods or trained workers using intact cores without laboratory analysis of all samples.

**Introduction**

Mapping and quantifying soil organic carbon (SOC) contents and distributions is crucial for modeling global carbon cycles. Unfortunately, direct measurement of soil carbon is expensive and time-consuming. Thus indirect and rapid assessments of SOC are of interest to both soil scientists and policy makers. These include semi-quantitative methods, such as loss on ignition (Konen et al., 2002) and thermogravimetry (Siewert, 2004), and remote sensing methods, such as aerial photography (Chen et al., 2005) and video imaging (Fox and Sabbagh, 2004). An easy method to predict SOC in many samples across landscapes and land uses will increase the understanding, prediction, and modeling efficiency of carbon distribution across fields, watersheds, and larger regions. This study seeks to find the most efficient and accurate methods of predicting SOC contents using soil color.

SOC exchanges with atmospheric carbon pools in response to changes in crop inputs, residue decomposition, erosion, and soil aggregate breakdown (Bruce et al., 1999; Stevenson and Cole, 1999). The numerous interactions between these factors create a complex gradient of SOC content over a landscape (Bird et al., 2001). Predictive mapping of SOC content is necessary to begin understanding SOC changes across and between landscapes (Bell et al., 2000). Soil carbon has been shown to be spatially dependent, varying laterally both by and within soil type and landscape position (Davis et al., 2004; Young and Hammer, 2000a,b; Walker et al., 1996). Soil carbon is also stratified vertically within a given soil. SOC content is greatest near the surface where biological inputs are greatest (Stevenson,
Therefore, the methods in which data are collected and aggregated can influence or even determine estimates of field and regional scale carbon cycles. To calculate total carbon changes on a field or regional scale, more efficient sampling and measurement schemes that lead to more accurate prediction of soil carbon are needed. Landscape-scale studies are needed to allow scaling-up of these models to regional or national scales (e.g. Groffman, 1991).

Direct measurement of SOC content can be expensive and time-consuming. It is complicated by the need for many samples to assess spatial heterogeneity (Bird et al., 1999). Soil color can serve as a cost effective proxy for determining organic-matter or SOC content (Konen et al., 2003; Schulze et al., 1993; Fernandez, 1988) on many samples across fields or landscapes. Soil color is one of the most obvious features of soil morphology and organic matter has long been known as one of the primary pigmenting agents in soil (Buol et al., 2003; Simonson, 1993; Robinson and McCaughey, 1911).

The Munsell color system is used for soil field descriptions in the United States (Schoenberger et al., 2002). Soil samples have traditionally been visually matched to a color chip with a given hue, chroma, and value. There is a long history of relating soil color to soil organic matter in the Midwest. Prior to the adoption of Munsell color system, Brown and O’Neal (1923) worked in Iowa, drawing the general conclusion that darker soils contain more organic matter. Alexander (1971) used a field color chart for estimating organic matter in Illinois. Steinhardt and Franzmeier (1979) estimated organic matter for cultivated soils in Indiana using field soil scientist Munsell colors. These studies were able to use soil color to group soils into broad categories, but failed to produce satisfactory predictive equations.
Fernandez and Schulze (1987) noted that visually matching soil to color chips was not an adequate predictor of organic matter concentrations.

Although soil color chips are standardized, there is still a certain amount of subjectivity and variability due to the influence of an individual human eye (Post et al., 1993). Fortunately, there are now affordable and rapid instruments that can quantify soil color reliably and accurately (Torrent and Barron, 1993). Konen et al. (2003) used such an instrument to develop satisfactory regressions between soil organic matter and color components on surface samples on the Des Moines Lobe, Iowa. Working in Indiana, Schulze et al. (1993) found that relationships between color and soil organic matter were similar for landscapes with same parent material and texture but not for those that differed significantly. Fernandez et al. (1988) found that color and organic matter were strongly correlated when calibrations were done on a field by field basis.

The majority of these SOC-soil color studies have focused on a limited number of soil surface samples from cultivated soil. It is known that SOC content is influenced by many factors including native vegetation, land use, management practices, soil properties, and topography (Bell et al., 2001; Follett, 2001; Franzlubber et al., 2000; Franzmeier et al., 1985; Jenny, 1980). Shields et al. (1968) found that Mollisols and Alfisols had differing soil color–organic matter relationships. Comparing SOC capacity to current levels requires evaluating SOC content across multiple land uses. Realizing the potential of carbon sequestration in soils depends on strengthening spatial databases of soil carbon pools under different land uses and management practices (Lal et al., 2001; Kern, 1994). The purpose of this study is to expand on previous work by evaluating various soil color measurement
techniques to predict SOC on surface and subsoil samples from two extensively sampled land uses, agriculture and prairie, in northeast Iowa.

**Materials and Methods**

**Study Area**

The study sites are on the Hayden Prairie State Preserve and an adjacent agricultural field in northeast Iowa (Figure 1). Most of the soils in this area are formed in one to two meters of Iowan Surface pedisediment, which overlies a thick, dense Pre-Illinoian glacial till (Prior, 1991; Buckner et al., 1974; Ruhe, 1969). Tallgrass prairie was the native vegetation for the past 8,000 to 9,000 years (Whitney, 1994; Thompson, 1992). Soils formed from Iowan Surface diamicton under tallgrass prairie are extensive in Iowa and southeastern Minnesota, with more than 80% of the area currently dedicated to row crop production (Iowa Department of Natural Resources, 2000). At 240 acres, Hayden Prairie is the largest prairie remnant on the Iowa Surface while the cropped field represents the area's predominant land use. The prairie and field provide an ideal contrast to evaluate the effects of a centuries worth of agricultural cultivation on SOC content and distribution across the landscape. Previous studies indicate that Iowa soils have potential to act as carbon sinks (Burras et al. 2005; Paustian et al., 2002). Studying this location provides an opportunity to expand on previous work on soil color and SOC in other areas of Iowa and beyond (Konen et al., 2003).

**Sampling**

Each land use was sampled in an unbalanced hierarchical nested grid. This was done to determine the scale of spatial dependence and improve sampling efficiency (Borgelt et al., 1997; Oliver and Webster, 1986). A square grid was created and georeferenced to minimize
the number of samples while assuring a range of spatial scales. A 24ha area of both the
prairie and agricultural field was divided into a 100m grid. This grid was separated into 6
blocks. Within each block, one 100m square was randomly selected for further division into
a nested grid. Each nested grid was composed of grid points that were 50, 25, 12.5, 5, and
2.5m apart. Cores (0.05m x 1.5m) were taken at each grid node with a truck mounted
Giddings hydraulic soil probe (Figure 2). There were a total of 203 cores taken in each land
use. Sixty-three of those cores, 100m grid samples and one randomly selected nested grid,
were analyzed for SOC (Table 1).

Field Description and Color Analysis

All 406 sampled cores were described using standard techniques and nomenclature
(Schoenberger et al., 2002). A portion of each horizon and depth increment was cut,
weighed, and oven dried to determine bulk density by a modified volumetric core method
(Konen, 1999; Soil Survey Staff, 1996). Soil color was determined through various
measurements schemes to ascertain the most accurate and efficient way to estimate SOC. A
summary of these techniques and their abbreviations is given in Table 2. Color
measurements were determined on horizons (H), depth increments (I), and individual
prepared samples (S) by Munsell Soil Color Book (B and D) and chroma meter (C). Soil
color was visually identified to the nearest hue value and chroma using the Munsell Soil
Color Book. Chroma meter color readings were taken with a Minolta CR-310 Chroma Meter
(Minolta Corp, Ramsey, NJ) with a CR-A33e glass light projection tube attachment to
measure Munsell hue, value and chroma.
The first color measurements were done on intact soil cores. Soil cores were placed in halved PVC pipes to ensure a common background for color analysis. Each core was cut in half with a sharp knife to assure sufficient surface area for a reading. This preparation is referred to as the split-core technique. If dry, the soil was then wetted with a spray bottle of water until no further change in color was observed, but not to the point of glistening (generally very little moisture was added, so cores would be considered field moist). Munsell Soil Color Book and chroma meter color readings were taken at the mid-point depth of each horizon (HB and HC) and predetermined depth increments (IB and IC) of 0-5, 5-10, 15-30, 30-50, and 50-100 cm. Soil color was then determined by Munsell Soil Color Book for the horizon matrix (HD) as in a traditional description (Schoenberger et al., 2002). Finally, the chroma meter was used to determine Munsell hue, value and chroma for moist (SCm) and dry (SCd) prepared samples as described under laboratory analysis.

Laboratory Analysis

Laboratory analyses, done on 100 m grid samples and one randomly selected nested grid, included pH, soil organic carbon, particle size determination, chroma meter color, and bulk density (Soil Survey Staff, 1996). A subset of these cores chosen to represent all landscape positions were also analyzed for particle size distribution. Soil particle size distribution was determined using the volumetric pipette procedure (Soil Survey Staff, 1996). Samples were divided by horizon and depth increment. Samples were then ground to pass a 2 mm sieve and analyzed for SOC, and chroma meter color. Chroma meter color measurement followed the procedure of Konen, et al. (2003). Samples were placed in 450 mL plastic cups to a depth of 3 cm. The chroma meter probe was placed vertically over the sample and pressed firmly to ensure a uniform flat surface. After air-dry measurements were
made (SCd), the sample was moistened until no further change in color was observed. Measurements were then taken on the moist surface (SCm). Soil organic carbon was determined by the Iowa State Soil Testing Laboratory. Total organic carbon was measured with a Leco LC2000 (Model CHN 600, LECO, St. Joseph, MI). Samples with pH > 7.5 were analyzed by acid injection (Sherrod et al., 2002) for inorganic carbon. That value was subtracted from total carbon to obtain the SOC values. Analyses were done on the SOC content of whole cores, horizons and depth increments. Regression was done using SAS system for windows V9.1 software (SAS Institute, 1999).

**Results and Discussion**

To complement the understanding of the differences between SOC and soil color relationships for these land uses, a summary of the general soil properties of each land use is given in Table 3. Of particular interest are bulk density and particle size distribution. Bulk density has a direct relationship to the volume of SOC in any given sample, horizon, or core. Epipedon samples have an average bulk density of 1.38 g cm$^{-3}$ in the agricultural field and 1.07 g cm$^{-3}$ in the prairie. Subsoil samples average 1.70 g cm$^{-3}$ for the agricultural field and 1.80 g cm$^{-3}$ for the prairie.

Particle size distribution has been shown to be related to SOC content (Konen et al., 2003; Franzmeier, 1998; and Nichols, 1984). Therefore, any relationship between texture and land use or color could affect the relationship between soil color and SOC. The average particle size distribution of epipedons is 32.4 % sand, 44.1 % silt, and 22.8% clay in the agricultural field and 25.6% sand, 48.2% silt, and 25.7% clay in the prairie. The subsoil horizons, 49.3 % sand, 28.2 % silt, and 22.5% clay in the agricultural field and 44.4% sand, 26.9% silt, and 28.7% clay in the prairie, are generally formed in glacial till and have
significantly greater sand content (agriculture $P = 0.0002$, prairie $P = <0.0001$) and less silt (agriculture $P = <0.0001$, prairie $P = 0.<0.0001$) than epipedons. Clay contents of epipedons and subsoils are not significantly different for either land use. Agricultural epipedons have significantly more sand (6.8%) and less clay (2.9%). In the subsoil only clay content is significantly different with the prairie having 28.7% clay and the agricultural field 22.5% clay (Table 3). However, the range of horizon particle size distribution is similar for the agriculture field and the prairie (Figure 2). Clay content is not significantly related to SOC content in epipedon horizons (agriculture $r^2 = 0.02$, prairie $r^2 = 0.13$) or all horizons (agriculture $r^2 = 0.06$, prairie $r^2 = 0.11$) (Figure 3a). This may simply be due to the small range of clay content relative to the wider range of SOC content. Sand content, which varies more greatly, has a greater coefficient of determination with SOC content (agriculture $r^2 = 0.46$, prairie $r^2 = 0.29$) (Figure 3b). This negative correlation is most likely due to the general decrease in SOC content with depth and the greater sand content in the subsoil, formed in glacial till, than in the epipedons, primarily derived from pedisediment and other surficial deposits. Therefore, we can conclude that particle size distribution is not controlling the distribution of SOC content in the study sites.

The range of SOC (g kg$^{-1}$ and kg m$^{-3}$) and soil color measurements are shown in Table 4. Color measurements are given for prepared samples, horizons, and depth increments. SOC content is significantly different between land uses while most soil color measurements are not significantly different. For instance, sample SOC content ranges from 0 - 48.2 (mean 10.1 SE 0.42) g kg$^{-1}$ in the agriculture field and 0 – 165.7 (mean 20.1 SE 1.09) g kg$^{-1}$ in the prairie ($P = < 0.0001$) but the moist value of ground samples ranges from
3.8 – 6.6 (mean 5.23 SE 0.01) g kg\(^{-1}\) in the agriculture field and 3.8-6.4 (mean 5.23 SE 0.02) g kg\(^{-1}\) in the prairie (P = 0.4700).

For the regression of soil color variables and SOC content, results are presented for individual Munsell value and Munsell chroma as well as the full model of each technique (combining of Munsell value, chroma and the depth of the sample, horizon, or depth increment). The coefficient of determination is shown for all soil color and SOC measurements in Table 5. Separating the measurements by land use improved the coefficient of determination in all cases, so those are the results presented throughout this paper. These analyses indicate that the relationship between soil color and SOC is fundamentally different for these two land uses. It has been documented that the composition of SOC is different for comparable land uses in Iowa (Zhang et al. 1988). Partitioning sample by horizon type (epipedon, subsoil etc.) does not improve the correlation of color and SOC.

**Prepared samples**

The best single factor predictors of SOC are moist Munsell value in the agriculture field (\(r^2 = 0.70\)) and dry Munsell value in the prairie (\(r^2 = 0.54\)) when used to predict the concentration (g kg\(^{-1}\)) of SOC per sample (P) (Figure 4a). When multiple factors are used, SCm, the full moist chroma meter model (moist Munsell value and chroma combined with the depth from which the sample was taken), produce the best results (agriculture \(r^2 = 0.77\), prairie \(r^2 = 0.56\)). The agriculture \(r^2\) are similar to those found by Konen et al. (2003). Analyzing only A horizons, they found a logarithmically decreasing relationship of \(r^2 = 0.77\) and \(r^2 = 0.68\) for SOC and dry and moist Munsell values respectively. Soil color does a poorer job of predicting SOC content by volume (kg m\(^{-3}\)), particularly in the prairie (Figure 4b). The best single factor predictor of SOC content by volume (kg m\(^{-3}\)) is moist Munsell
value for both land uses (agriculture $r^2 = 0.65$; prairie $r^2 = 0.10$). The full moist chroma meter models, SCm, had $r^2$ of 0.73 in the agriculture field and 0.11 in the prairie.

Transforming SOC by log(10) results in a more normal distribution of SOC values and increases the coefficient of determination for most relationships. Coefficient of determination of moist Munsell value in the agriculture field ($r^2 = 0.72$) and dry Munsell value in the prairie ($r^2 = 0.72$) improves with log transformation of SOC content by weight (g kg$^{-1}$) (Figure 4c and 4d). When multiple factors are used, the full model from moist chroma meter analysis, SCm, still produces the best prediction results (agriculture $r^2 = 0.81$, prairie $r^2 = 0.75$). The greatest improvements from log transformations are seen for SOC by volume (kg m$^{-3}$) in the prairie. The full model of moist chroma meter and log SOC (kg m$^{-3}$) improves from $r^2 = 0.11$ for non-transformed SOC values to $r^2 = 0.65$ for log transformed SOC. The ability to predict SOC on a weight for volume basis would allow monitoring of SOC content without bulk density measurements.

**Horizons**

Evaluating color by horizon does not require grinding samples or even removal of cores from the field. This would allow easier, more rapid assessment than the prepared sample technique. For analysis by horizon, sample SOC values were grouped by horizon and averaged, weighted by volume. The best individual predictors of horizon SOC (H) by weight (g kg$^{-1}$) for the agriculture field were HB values, book Munsell values taken on the split cores at horizon midpoints, ($r^2 = 0.70$), and HD values, Munsell values from traditional description techniques, ($r^2 = 0.69$). For prairie horizons, HD values and chromas were the best predictors of SOC (g kg$^{-1}$) content ($r^2 = 0.47$). HB color measurements have only slightly lower coefficients of determination (value $r^2 = 0.46$, chroma $r^2 = 0.45$). The full HD
model, combining book description Munsell value and chroma with horizon depth, results in the greatest coefficients of variation; $r^2 = 0.79$ for the agriculture field and $r^2 = 0.53$ for the prairie (Figure 5). Taking chroma meter measurements on these samples did not improve the relationship between soil color and SOC. In fact, the full HC model, combining chroma meter Munsell value and chroma with depth, does a poorer job of explaining SOC (g kg$^{-1}$) than the full HD or HB models: prairie $r^2 = 0.44$, and agriculture $r^2 = 0.70$. Once again, SOC by volume (kg m$^{-3}$) has a weaker correlation with soil color than SOC by weight (g kg$^{-1}$). However, the rank of models remains the same. For the agriculture field, the best individual predictors of horizon SOC by volume (kg m$^{-3}$) were HB and HD values ($r^2 = 0.60$). As with SOC by weight, HC (full model $r^2 = 0.61$) does a poorer job of explaining SOC by volume(kg m$^{-3}$) than the HD (full model $r^2 = 0.69$) or HB (full model $r^2 = 0.68$) models. For prairie horizons, the relationships are not significant for SOC content by volume (kg m$^{-3}$) for any individual color measurement.

Transforming horizon SOC by log(10) results in a more normal distribution of values and increases the coefficient of determination for most relationships in the agriculture field and all color measurements in the prairie. The best single predictor of log transformed SOC content by weight (g kg$^{-1}$) or volume (kg m$^{-3}$) is HD value for both the agricultural field ($r^2 = 0.65, 0.62$) and the prairie ($r^2 = 0.60, 0.48$). The full HD model is also the best overall predictor for each land use: weight (g kg$^{-1}$) (agriculture $r^2 = 0.81$, prairie $r^2 = 0.68$), and volume (kg m$^{-3}$) (agriculture $r^2 = 0.76$, prairie $r^2 = 0.53$) (Figure 5). Chroma meter relationships are markedly improved by log transformation of SOC content. The full HC model has $r^2$ of 0.76 (g kg$^{-1}$) and 0.72 (kg m$^{-3}$) in the agriculture field and 0.58 (g kg$^{-1}$) and 0.44 (kg m$^{-3}$) in the prairie.
Depth Increments

The most rapid method of soil color taken was done by predetermined depth increments. Color was determined on spit cores with a chroma meter (IC) and Munsell Soil Color Book (IB). This method does not require extensive soil description training or laboratory analyses. For individual factors, the greatest coefficient of determination for regression with SOC by weight (g kg$^{-1}$) in the agriculture field is IB value, soil color book Munsell values taken on the split cores at depth increment midpoints, ($r^2 = 0.68$). For prairie depth increment, the best individual relationship was for IB chroma ($r^2 = 0.51$). The full IB model, soil book color measurements, and IC model, chroma meter measurements, are similar for the agriculture field ($r^2 = 0.76$, $r^2 = 0.74$), but IB are better for the prairie ($r^2 = 0.51$, $r^2 = 0.23$)(Figure 7). Once again, the relationship between SOC and soil color is much less significant for prairie measurements.

Unlike prepared samples and horizons, depth increment (I) SOC content by volume (kg m$^{-3}$) has a better correlation with soil color than SOC by weight (g kg$^{-1}$). For individual factors the same color components have the greatest coefficient of determination for regression with depth increment SOC by volume (kg m$^{-3}$) as SOC by weight (g kg$^{-1}$). In the agriculture field, IB value has the highest $r^2$ (0.71). For prairie depth increments, the best individual relationship is for IB chroma ($r^2 = 0.53$). The full models are similar for the agriculture field (IC $r^2 = 0.74$, IB $r^2 = 0.76$), and for the prairie (IC $r^2 = 0.52$, IB $r^2 = 0.57$). The relationship between SOC by volume (kg m$^{-3}$) and soil color is much greater for depth increments than other color measurement techniques.

Transforming depth increment SOC by log(10) increases the coefficient of determination for most relationships in the agriculture field and all color measurements in the
prairie. The best single predictor of log transformed SOC content by weight (g kg\(^{-1}\)) is IC value in the agriculture field (\(r^2 = 0.65\)) and IB chroma in the prairie (\(r^2 = 0.61\)). When predicting the log transformation of SOC by volume (kg m\(^{-3}\)), IB has the highest coefficient of variations for both the agriculture field (\(r^2 = 0.63\)) and the prairie (\(r^2 = 0.63\)). The full models of soil color book (IB) and chroma meter (IC) are identical (or nearly so) for log transformed SOC by weight (g kg\(^{-1}\)) and volume (kg m\(^{-3}\)). In the agriculture field, \(r^2\) is 0.86 for both full models and log transformed SOC by weight and volume regressions, while the prairie regression has \(r^2\) of 0.61 for the full IC model and 0.62 for the full IB model (Figure 7).

Comparing Techniques

Torrent and Barron (1993) found that carefully prepared samples had the best SOC-soil color relationships due to the ability to control the conditions of measurement. In this study, the analysis of prepared samples most closely follows their recommendations. SOC and soil color measurements are being made on sub-samples of a sample under controlled moisture conditions. However, we found traditional description or split-core colors at horizon or depth increment midpoints produced similar results. The four types of soil color measurements, (chroma meter on ground samples (SCd&m), chroma meter at midpoints (HC and IC), soil color book at midpoints (HB, IB), and descriptions of horizon matrix (HD) resulted in similar coefficients of variations in the agriculture field for both SOC by weight (g kg\(^{-1}\)) and volume (kg m\(^{-3}\)). In the prairie, chroma meter had consistently lower coefficient of determinations for non-transformed SOC contents. The best coefficient of determination is for SOC by weight (g kg\(^{-1}\)) and the full HD model, combined description Munsell value and chroma with horizon depth, for both the agriculture field (\(r^2 = 0.79\)) and the prairie (\(r^2 = \))
The lowest coefficient of determination is for SOC by volume (kg m$^{-3}$) and HC (agriculture $r^2 = 0.61$, prairie $r^2 = 0.05$). All models have a common shortcoming, they do not predict equally well at all ranges of SOC content. The most linear predictor was for the full IC model.

Log transformation of agriculture SOC increases most individual measurement $r^2$ values and results in depth increment colors, IB and IC, having slightly higher $r^2$ values than horizon or prepared sample colors. The best overall $r^2$ values are for IC and IB in the agriculture field (weight $r^2 = 0.86$, volume $r^2 = 0.84$) and IB for the prairie (weight $r^2 = 0.72$, volume $r^2 = 0.62$). There is a much smaller range in $r^2$ for transformed SOC predictions. The lowest coefficient of determinations for transformed SOC is for the regression of SOC by volume (kg m$^{-3}$) and HD (agriculture $r^2 = 0.76$, prairie $r^2 = 0.53$). The prediction of transformed SOC content with IC still has a bias (Figures 6). Predicting SOC content with these equations underestimates the highest SOC contents. There appears to be a saturation point at approximately 50 kg m$^{-3}$ SOC past which the SOC-soil color relationship is no longer applicable.

**Conclusions**

Soil color provides a rapid and useful method of predicting SOC content. Separating samples by land use improved predictions while separating them by diagnostic horizons did not. The relationships between SOC and soil color differs for the agriculture field and the prairie. These differences indicate that separate relationships will need to be developed for each land use when applying these predictions techniques. Further study is needed to explore the differences in the soil color-SOC relationships within and between land uses.
All three sampling techniques evaluated, prepared samples (S), horizons (H), and depth increments (I), combined with the four types of soil color measurements, (chroma meter on ground samples (SCd&m), chroma meter at midpoints (HC and IC), soil color book at midpoints (HB, IB), and descriptions of horizon matrix (HD)Munsell Soil Color Book and chroma meter colors with SOC, yielded significant regression relationships with SOC contents. The best predictors of SOC were HD for SOC by weight (g kg$^{-1}$) (agriculture r$^2$ = 0.79, prairie r$^2$ = 0.53), HB for SOC by volume (kg m$^{-3}$) (agriculture r$^2$ = 0.76, prairie r$^2$ = 0.57), and IC and IB for log transformed SOC by weight and volume (agriculture r$^2$ = 0.84, prairie r$^2$ = 0.62).

This study indicates that SOC content predictions could be made on field measurements, by soil scientists using traditional survey methods or trained workers using the split-core technique, without laboratory analysis of all samples. Description of soil color is a standard part of the soil survey and soil research process. Using these colors to predict SOC contents would allow us to estimate SOC contents from previous data sets. However, many questions involving SOC are site specific and require a detailed assessment of SOC distribution across the landscape. As horizons are sometimes difficult to separate before disturbing the split core, and reasonable soil scientists have been known to disagree on their breaks, taking measurements at predetermined depth increments provides a quick, easily comparable alternative. The split-core technique provides a simple, rapid assessment of soil color that can be done in the field or the laboratory. Both soil color book and chroma meter, provide feasible methods of determining color of the depth increments of split cores. Munsell Soil Color Books are relatively cheap, easily transported, and easy to use with a little training. Their primary drawback is the variation in individual perception of soil color.
Chroma meter measurement would eliminate this problem, and improve the ability to compare results between studies. However, chroma meters are substantially more expensive than Munsell Soil Color Book and require a power source, battery or outlet, to operate. The preference between these techniques would depend on sample numbers, monetary recourses, and the comfort of the investigator with each technique.

References


Table 1. Soil series and great group classification of cores analyzed for soil organic carbon content and soil color in the agricultural field and the prairie.

<table>
<thead>
<tr>
<th>Soil Series</th>
<th>Great Group</th>
<th>Cores Analyzed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Clyde</td>
<td>Typic Endoaquoll</td>
<td>agriculture 5</td>
</tr>
<tr>
<td></td>
<td></td>
<td>prairie 3</td>
</tr>
<tr>
<td>Cresco</td>
<td>Typic Argiudoll</td>
<td>agriculture 19</td>
</tr>
<tr>
<td></td>
<td></td>
<td>prairie 36</td>
</tr>
<tr>
<td>Floyd</td>
<td>Aquic Hapludoll</td>
<td>agriculture 27</td>
</tr>
<tr>
<td></td>
<td></td>
<td>prairie 7</td>
</tr>
<tr>
<td>Jameston</td>
<td>Typic Argiaquolls</td>
<td>agriculture 2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>prairie 2</td>
</tr>
<tr>
<td>Kenyon</td>
<td>Typic Hapludoll</td>
<td>agriculture 2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>prairie 2</td>
</tr>
<tr>
<td>Ostrander</td>
<td>Typic Hapludoll</td>
<td>agriculture 5</td>
</tr>
<tr>
<td></td>
<td></td>
<td>prairie 4</td>
</tr>
<tr>
<td>Protivin</td>
<td>Aquic Argiudoll</td>
<td>agriculture 4</td>
</tr>
<tr>
<td></td>
<td></td>
<td>prairie 11</td>
</tr>
<tr>
<td>Schley</td>
<td>Udollic Endoaqualf</td>
<td>agriculture 1</td>
</tr>
</tbody>
</table>

† Soil series and great group as mapped in Howard County Soil Survey (Iowa Cooperative Soil Survey, 2003, Soil Taxonomy, 1999).

Table 2. Summary table of abbreviations used for soil organic carbon content and color measurement combinations.

<table>
<thead>
<tr>
<th>Technique</th>
<th>Measured on:</th>
<th>Measured by:</th>
<th>Abbreviation:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prepared Sample†</td>
<td>ground &lt;2mm air dry</td>
<td>Chroma meter</td>
<td>SCd</td>
</tr>
<tr>
<td></td>
<td>ground &lt;2mm moist Chroma</td>
<td></td>
<td>SCm</td>
</tr>
<tr>
<td>Horizon Description‡</td>
<td>ped matrix moist Munsell</td>
<td>HD</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Soil Color Book</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Horizon Midpoint§</td>
<td>Split - core moist Munsell</td>
<td>HB</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Soil Color Book Chroma</td>
<td>HC</td>
<td></td>
</tr>
<tr>
<td></td>
<td>meter</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Depth Increment Midpoint</td>
<td>Split - core moist</td>
<td>IB</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Munsell Soil Color Book</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Chroma meter</td>
<td>IC</td>
<td></td>
</tr>
</tbody>
</table>

† Prepared samples were are dried and crushed to pass through a <2mm.
‡ Horizon description follows standard description techniques (Schoenberger et al., 2002).
§ Horizon midpoint and depth increment midpoint colors were taken on whole cores that had been split in half lengthwise.
Table 3. Summary of epipedon and subsoil properties for agricultural field and prairie. †

<table>
<thead>
<tr>
<th>Property</th>
<th>Agriculture</th>
<th>Prairie</th>
<th>P&gt;f §</th>
</tr>
</thead>
<tbody>
<tr>
<td>Epipedon</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bulk Density g cm⁻³</td>
<td>1.38 0.02</td>
<td>1.07 0.01</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>pH</td>
<td>5.9 0.06</td>
<td>5.22 0.1</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>WSA %</td>
<td>27.4 1.7</td>
<td>63.9 1.8</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>Sand %</td>
<td>32.4 2.0</td>
<td>25.6 2.0</td>
<td>0.0221</td>
</tr>
<tr>
<td>Silt %</td>
<td>44.1 1.5</td>
<td>48.2 1.7</td>
<td>0.0734</td>
</tr>
<tr>
<td>Clay %</td>
<td>22.8 1.0</td>
<td>25.7 0.8</td>
<td>0.0368</td>
</tr>
<tr>
<td>Subsoil</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bulk Density g cm⁻³</td>
<td>1.71 0.03</td>
<td>1.80 0.02</td>
<td>0.0204</td>
</tr>
<tr>
<td>pH</td>
<td>6.5 0.1</td>
<td>5.9 0.1</td>
<td>0.0001</td>
</tr>
<tr>
<td>Sand %</td>
<td>46.1 2.7</td>
<td>43.2 2.6</td>
<td>0.4441</td>
</tr>
<tr>
<td>Silt %</td>
<td>27.9 2.0</td>
<td>26.3 1.2</td>
<td>0.5050</td>
</tr>
<tr>
<td>Clay %</td>
<td>22.5 1.5</td>
<td>28.7 1.5</td>
<td>0.0058</td>
</tr>
</tbody>
</table>

† All horizons with matrix color <3 Munsell value and chroma were considered to be a part of the epipedon.
‡ SE, standard error; WSA, water stable aggregate content.
§ P>f values for Anova of soil property land use means.
Table 4. Ranges of soil organic carbon content and Munsell soil color measurements taken with chroma meter and Munsell Soil Color Book for the agricultural field and prairie.

<table>
<thead>
<tr>
<th>Prepared Sample</th>
<th>Horizon</th>
<th>Depth Increment</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Ag †</td>
<td>Pr</td>
</tr>
<tr>
<td>SOC</td>
<td>min</td>
<td>max</td>
</tr>
<tr>
<td>g kg⁻¹</td>
<td>0</td>
<td>48.2</td>
</tr>
<tr>
<td>kg m⁻³</td>
<td>0</td>
<td>77.6</td>
</tr>
<tr>
<td>SCd ‡ Value</td>
<td>3.8</td>
<td>6.6</td>
</tr>
<tr>
<td>Chroma</td>
<td>0.9</td>
<td>3.5</td>
</tr>
<tr>
<td>HD Value</td>
<td>1</td>
<td>7</td>
</tr>
<tr>
<td>Chroma</td>
<td>0</td>
<td>6</td>
</tr>
<tr>
<td>HC &amp; IC Value</td>
<td>3.2</td>
<td>4.8</td>
</tr>
<tr>
<td>Chroma</td>
<td>1.2</td>
<td>4.0</td>
</tr>
<tr>
<td>HB &amp; IB Value</td>
<td>2</td>
<td>6</td>
</tr>
<tr>
<td>Chroma</td>
<td>0</td>
<td>6</td>
</tr>
</tbody>
</table>

† Ag, agricultural; Pr, prairie; SOC, soil organic carbon, min., minimum; max., maximum.
‡ Color technique abbreviations: SCd, chroma meter color of air dry prepared samples; HD, horizon color using standard description techniques; HC, chroma meter color at horizon midpoint; HB, Munsell soil color book color at horizon midpoint; IC, chroma meter color at horizon midpoint; IB, Munsell soil color book color at horizon midpoint.
Table 5. Table of coefficient of determination values for linear regression of soil organic carbon content measured by original and transformed weight and volume with individual Munsell soil color measurements and the full models for each: a) models using prepared samples and horizon description colors, b) horizon and depth increment midpoint color measured on split-cores. * †

<table>
<thead>
<tr>
<th>Color Measurement</th>
<th>SOC Content Measurement</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>Technique ‡</td>
<td>Model</td>
</tr>
<tr>
<td><strong>Prepared Sample</strong></td>
<td><strong>SCd</strong> Value</td>
</tr>
<tr>
<td></td>
<td>Chroma</td>
</tr>
<tr>
<td></td>
<td><strong>Full</strong></td>
</tr>
<tr>
<td><strong>Horizon Description</strong></td>
<td><strong>SCm</strong> Value</td>
</tr>
<tr>
<td></td>
<td>Chroma</td>
</tr>
<tr>
<td></td>
<td><strong>Full</strong></td>
</tr>
<tr>
<td><strong>HB</strong></td>
<td>Value</td>
</tr>
<tr>
<td></td>
<td>Chroma</td>
</tr>
<tr>
<td></td>
<td><strong>Full</strong></td>
</tr>
</tbody>
</table>
Table 5. continued.
b) Horizon and Depth Increment Midpoint

<table>
<thead>
<tr>
<th>Color Measurement</th>
<th>SOC Content Measurement</th>
</tr>
</thead>
<tbody>
<tr>
<td>Technique</td>
<td>Model</td>
</tr>
<tr>
<td></td>
<td>Ag</td>
</tr>
<tr>
<td>Horizon Midpoint</td>
<td></td>
</tr>
<tr>
<td>HB</td>
<td>Value</td>
</tr>
<tr>
<td></td>
<td>Chroma</td>
</tr>
<tr>
<td></td>
<td>Full</td>
</tr>
<tr>
<td>HC</td>
<td>Value</td>
</tr>
<tr>
<td></td>
<td>Chroma</td>
</tr>
<tr>
<td></td>
<td>Full</td>
</tr>
<tr>
<td>Depth Increment Midpoint</td>
<td></td>
</tr>
<tr>
<td>IB</td>
<td>Value</td>
</tr>
<tr>
<td></td>
<td>Chroma</td>
</tr>
<tr>
<td></td>
<td>Full</td>
</tr>
<tr>
<td>IC</td>
<td>Value</td>
</tr>
<tr>
<td></td>
<td>Chroma</td>
</tr>
<tr>
<td></td>
<td>Full</td>
</tr>
</tbody>
</table>

* all are significant at 0.05 level.
† Models are for SOC content equal: value (Munsell value only), chroma (Munsell chroma only), and full (Munsell value, chroma and measurement depth).
‡ Ag, agriculture; Pr, prairie; SOC, soil organic carbon;
§ Color measurement techniques: SCd, chroma meter color of air dry prepared samples; SCm chroma meter color of moist prepared samples, HD, horizon color using standard description techniques; HC, chroma meter color at horizon midpoint; HB, Munsell Soil Color Book color at horizon midpoint, HC, chroma meter color at horizon midpoint; HB, Munsell soil color book color at horizon midpoint.
Figure 1. Location of study site on the Iowan Surface in northeastern Iowa, USA. Locations of all described cores, laboratory analyzed cores, and selected texture cores are shown on an aerial photograph.
Figure 2. Average particle size distribution of analyzed epipedon and subsoil horizons in the agricultural field and prairie. Epipedons include all horizons that were a part of the epipedon and subsoils include all horizons beneath the epipedon.
a) Clay

\[ \text{SOC} = 0.50(\text{clay}) + 1.56 \]
\[ R^2 = 0.06 \]

\[ \text{SOC} = -1.70(\text{clay}) + 70.77 \]
\[ R^2 = 0.11 \]

b) Sand

\[ \text{SOC} = -0.52(\text{sand}) + 33.11 \]
\[ R^2 = 0.46 \]

\[ \text{SOC} = -0.97(\text{sand}) + 56.50 \]
\[ R^2 = 0.29 \]

Figure 3. Regression of soil organic carbon (SOC) with a) clay and b) sand content.
Figure 4. Soil organic carbon content (SOC) and prepared sample chroma meter Munsell values for a) SOC (g kg\(^{-1}\)), b) SOC (kg m\(^3\)), c) log SOC (g kg\(^{-1}\)), and d) Log SOC (kg m\(^3\)).
Dry values were used for prairie and moist values for agricultural samples.
a) SOC (g kg\(^{-1}\))

Agriculture

\[
\text{SOC} = 33.96 - 0.01 (\text{depth}) - 4.39 (\text{value}) - 2.09 (\text{chroma})
\]

\[r^2 = 0.79\]

Prairie

\[
\text{SOC} = 50.00 - 0.12 (\text{depth}) - 4.86 (\text{value}) - 3.96 (\text{chroma})
\]

\[r^2 = 0.53\]

b) log SOC (kg m\(^{-3}\))

Agriculture

\[
\text{log SOC} = 1.95 - 0.01 (\text{depth}) - 0.16 (\text{value}) - 0.07 (\text{chroma})
\]

\[r^2 = 0.76\]

Prairie

\[
\text{log SOC} = 1.92 - 0.002 (\text{depth}) - 0.17 (\text{value}) - 0.07 (\text{chroma})
\]

\[r^2 = 0.53\]

Figure 5. Actual and predicted soil organic carbon (SOC) content using horizons: a) SOC (g kg\(^{-1}\)) and b) Log SOC (kg m\(^{-3}\)). Predictions made with full horizon description model (HD), Munsell value, chroma and horizon depth for prairie and agricultural field.
a) agriculture

\[
\text{SOC} = 21.04 - 0.23(\text{depth}) - 6.01(\text{value}) + 17.95(\text{chroma}) \\
r^2 = 0.76
\]

\[
\text{Log SOC} = 1.73 - 0.01(\text{depth}) - 0.17(\text{value}) + 0.24(\text{chroma}) \\
r^2 = 0.84
\]

b) prairie

\[
\text{SOC} = 23.27 - 0.36(\text{depth}) - 0.06(\text{value}) + 12.41(\text{chroma}) \\
r^2 = 0.53
\]

\[
\text{Log SOC} = 1.73 - 0.01(\text{depth}) - 0.17(\text{value}) + 0.24(\text{chroma}) \\
r^2 = 0.60
\]

Figure 6. Actual and predicted SOC content by volume (kg m\(^{-3}\)) using depth increments: a) agricultural field and b) prairie. Predictions made using transformed and non-transformed prediction equations for the full IC model which uses chroma meter Munsell value, chroma, and increment depth from the midpoint of predetermined depth increments.
CHAPTER 6. SOIL ORGANIC CARBON PREDICTIONS USING COLOR, GIS, AND GEOSTATISTICS

A paper to be submitted to Soil Science Society of America Journal

Skye A. Wills, Jonathan A. Sandor, and C. Lee Burras

Abstract

Mapping and quantifying soil organic carbon content (SOCC) and its distribution are important for modeling and understanding local and global carbon cycles. The purpose of this study is to evaluate the use of multiple GIS and geostatistical techniques to predict SOCC on a native prairie and agricultural field along with previously established relationships between soil color and SOCC. Each land use was sampled on an unbalanced hierarchical nested grid for a total of 203 cores. Color was determined for all cores by Munsell Color Book and chroma meter. SOCC was determined to a depth of 0.2m and 1.0m on a subset of 63 cores. A training set, 75% of cores, was used to develop SOCC prediction models by soil map unit, landscape position, terrain attributes, ordinary kriging and co-kriging. The remaining cores were used to validate each model with regression of actual and predicted models. Topographic Wetness Index was the best predictor for both depths in the agriculture field \( r^2 = 0.52 \) and 0.66 while two other models best predicted SOCC in the prairie: ordinary kriging of measured values for 0.2m \( r^2=0.69 \), and co-kriging with chroma meter colors for 1.0m \( r^2=0.25 \). Average land use SOCC predictions vary by 2.40 kg m\(^{-2}\) to a depth of 0.2m and 3.84 kg m\(^{-2}\) to 1.0m in the agriculture field and 6.18 kg m\(^{-2}\) to 0.2m and 19.04 kg m\(^{-2}\) to 1.0m in the prairie. These differences are considerable and the model chosen will have considerable impact on research conclusions or management decisions made from SOCC predications.
Introduction

Soil organic carbon (SOC) is of interest for many reasons. It is often indicative of soil health and management sustainability. It is one of the most commonly chosen indicators of soil quality (Reeves, 1997). Soil organic matter, which contains SOC, has been shown to play a key role in soil tilth and productivity (Tisdall and Oades, 1982; Ulery et al., 1995). It can influence soil warming rates, water retention, and nutrient exchange (Buol et al, 2003; Stevenson, 1994). Soil organic carbon also has an important role in biogeochemical cycles and environmental quality. The amount and types of SOC affect bioactivity and bioavailability of heavy metals and organic pesticides (Stevenson and Cole, 1999; Pierzynski et al., 1994; Stevenson, 1994). SOC is considered an important pool for carbon storage and exchange with atmospheric carbon dioxide as well. Mapping and quantifying soil organic carbon contents (SOCC) and distributions are important for modeling and understanding global carbon cycles. There is interest in quantifying and modeling soil carbon, as many have shown that soils can “sequester” or act as carbon sinks (e.g. Lal, 2002, Hanson et al., 2001). Unfortunately, direct measurement of soil carbon is expensive and time-consuming. An easy method to predict SOCC across landscapes and land uses will increase the understanding, prediction, and modeling efficiency of carbon distribution across fields, watersheds, and larger regions.

The purpose of this study is to evaluate the use of multiple GIS and geostatistical techniques to predict SOCC on a native prairie and agriculture field. We use GIS classes from digital soil series map units and landscape position maps, derived terrain attributes, and geostatistical techniques to predict SOCC across both land uses. Previously determined relationships between SOC and soil color (Chapter 5) will be used to improve each of these
prediction strategies. Finally, we will compare the predicted values and errors from each land use and technique.

Soil color has long been used to predict organic matter and SOC with varying results (Fernandez, 1988; Konen et al., 2003; Schulze et al., 1993). Soil color is one of the most obvious features of soil morphology and organic matter has long been known as one of the primary pigimenting agents in soil (Buol et al., 2003; Robinson and McCaughey, 1911; Simonson, 1993). While using soil color to predict SOCC might reduce costs by allowing prediction without laboratory measurements, it does not reduce the number of samples that must be collected or predict in locations where samples are not taken. For this, soil color must be integrated with other prediction techniques. In this study, we will use previously established relationships between soil color and SOCC along with GIS and geostatistical models to improve SOCC prediction.

GIS can be used to group like things and represent them through maps. These maps can then be used as a predictive tool. Soil organic carbon content can be related to the properties that are used to delineate soil series polygons such as drainage class. Known information about a map unit can be used to extrapolate those properties to similar map units across landscapes and regions (Bouma et al., 1999; Burke et al., 1989; Voltz and Webster, 1990). Soil series has been used to predict SOC in large scale studies. Burke et al., (1989) quantified soil carbon across the United States using digitized soil maps. In Iowa, Paustian et al. (2002) used parameters from digital soil maps in carbon model simulations. For this study, we used published soil series boundaries (ICSS, 2003) along with our measurements to predict SOCC across the prairie and agriculture field.
Soil properties can also be related and predicted by landscape position. Studies have shown there to be a relationship between SOC and landscape position (Aguilar et al., 1988; Brubaker et al., 1994; Young and Hammer, 2000). Landscape positions can be identified in the field using simple models such as Ruhe’s (1975). While this may be practical for on-site field managers, it does not allow remote extrapolation of properties to a wider area. There are no widely available maps, as there are for soils, which can be used to convey landscape position properties across the landscape. With this in mind, we digitized landscape position maps across both land uses and used them to group SOCC measurements and make predictions across each.

Landscape positions are not always discrete and their identification in the field is subjective (Gerrard, 1981). To counter these problems, researchers are developing objective methods of defining and using landscape positions continuously across the landscape. Pennock et al., (1994) used statistically selected landform-soil complexes to improve the assessment of human activity on soil properties. Relative elevation and slope shape can serve as a proxy for landscape position designation. Digital elevation models can be used to derive terrain attributes that can be used to predict soil properties (Moore et al., 1991; Odeh et al., 1994). Gessler et al. (2000) used digital elevation models along with hydrologic parameters to select pedons for sampling and prediction of soil carbon. Ventura and Irvin (2000) used automated fuzzy set algorithms to classify areas into landscape positions based on properties including slope, curvature, and elevation. As techniques for elucidating landscape position improve, describing soil properties with them will become more profitable. We derived terrain attributes with a standard GIS application platform and used those attributes to model and predict SOCC across the agricultural field and the prairie.
Geostatistics are the branch of statistics dealing with spatial phenomena in the earth sciences (Journel, 1985). Geostatistics rest on the principle that things that are closer together are more alike than things that are farther apart. This central theme of geostatistics is known as the regionalized variable theory and the complementary function is known as a semi-variogram (Burgess and Webster, 1980a). Kriging uses the semi-variogram to predict values at unobserved location using minimization of errors (Krige, 1966). These principles have been applied to soil science for over two decades (e.g. Burgess and Webster, 1980a,b; Webster and Burgess, 1980a,b). New computer applications have allowed more wide-spread development and use of geostatistical techniques. However, there are still many applications of geostatistics that have yet to be explored. We used geostatistics to compare the distribution of soil properties across the prairie and agriculture field (Chap 3). In this paper, we use those geostatistical tools to predict SOCC across these land uses.

Geostatistics provide a powerful tool for analyzing spatially dependent data. However, many points are needed to calculate the semi-variogram (Webster and Oliver, 2001). To increase efficiency, more easily obtained data may be correlated with expensive lab measurements (Goovaerts, 1999; Vauclin et al., 1983). With co-kriging, related variables, such as soil color, can be used to improve predictions with more extensive data sets. This study combines soil color and SOCC measurements to expand the area that can be sampled and modeled using geostatistics.
Materials and Methods

Study Area

The study sites are on the Hayden Prairie State Preserve and an adjacent agricultural field in northeast Iowa (Figure 1). Most of the soils in this area are formed in one to two meters of Iowan Surface pedisediment, which overlies a thick, dense Pre-Illinoian glacial till (Prior, 1991; Russell, 1974, Ruhe, 1969;). Tallgrass prairie was the native vegetation for the past 8,000 to 9,000 years (Thompson, 1992). Soils formed from this combination of the Iowan Surface deposits and tallgrass prairie are extensive in Iowa and southeastern Minnesota, with more than 80% of the area currently dedicated to row crop production (IDNR, 2000). Hayden Prairie is perhaps the only remaining large prairie remnant on the Iowa Surface while the cropped field represents the region’s predominant land use. The prairie and field provide an ideal contrast to evaluate the effects of decades’ worth of agricultural cultivation on soil property distribution.

Sampling

Each land use was sampled in an unbalanced hierarchical nested grid. Six nests were randomly distributed across each land use independently. This was done to determine the scale of spatial dependence and improve sampling efficiency (Borgelt et al., 1997; Oliver and Webster, 1986). Cores were taken on a square grid, created and georeferenced to minimize the number of samples while assuring a range of spatial scales. A 24 ha area of both the prairie and agricultural field was divided into a 100m grid. This grid was separated into 6 blocks. Within each block, one 100m square was randomly selected for further division into a nested grid. Each nested grid was composed of grid points that were 50, 25, 12.5, 5, and
2.5m a part (Figure 1). Cores (0.05m x 1.5m) were taken at each grid node with a truck mounted Giddings hydraulic soil probe (Figure 2). A total of 203 cores were taken in each land use. Sixty-three of those cores were selected for laboratory analysis.

**Field Description and Color Analysis**

All 406 sampled cores were described using standard techniques and nomenclature (Schoenberger et al., 2002). A portion of each horizon and depth increment was cut, weighed, and oven dried to determine bulk density by a modified volumetric core method (Konen, 1999; Soil Survey Staff, 1996). Soil color was determined through various measurements schemes to determine the most accurate and efficient way to estimate SOC.

Two methods of soil color determination were used for this paper, referred to as description and chroma meter color. Chroma meter color readings were taken with a Minolta CR-310 Chroma Meter (Minolta Corp, Ramsey, NJ) with a CR-A33e glass light projection tube attachment to measure Munsell hue, value and chroma as used by Konen et al. (2003). Soil cores were placed in halved PVC pipes to ensure a common background for color analysis. Each core was cut in half with a sharp knife to assure sufficient surface area for a reading, referred to as split-cores. The core was then wetted with a spray bottle of water until no further change in color was observed, but not to the point of glistening. Chroma meter color readings were taken at the mid-point depth of each predetermined depth increments of 0-5, 5-10, 15-30, 30-50, and 50-100cm. For description colors, color of the horizon matrix was visually identified on individual peds to the nearest hue value and chroma using the Munsell Soil Color Book (Schoenberger et al., 2002).
Laboratory Analysis

Laboratory analyses were done on samples from the 100m grid cores and one randomly selected nested grid from each land use (63 cores from each land use). These cores will be referred to from this point on as laboratory cores. These analyses included pH, soil organic carbon, chroma meter color, water stable aggregate content, and surface horizon texture (Soil Survey Staff, 1996). A subset of these cores, chosen to represent all landscape positions, was also analyzed for particle size distribution. Samples were divided by horizon and depth increment for each core analyzed. Samples were ground to pass a 2mm sieve for further analysis.

Soil organic carbon was determined by the Iowa State Soil Testing Laboratory. Total organic carbon was measured with a Leco LC2000 (Model CHN 600, LECO, St. Joseph, MI). Samples with pH >7.5 were analyzed by acid injection (Sherrod et al., 2002) to determine inorganic carbon content. That value was subtracted from total carbon to determine the SOC content of each sample. Those values were multiplied by the bulk density of that sample to obtain a weight per volume SOCC. These values were summed to a depth of 0.2 and 1.0m for each core. Those are the values used in the prediction and validation analysis.

Statistical Analysis

Soil color, landscape positions, soil series map units, topographic wetness index, ordinary kriging and co-kriging were used to predict SOCC. GIS and geostatistical analyses were done with the GIS software ArcGIS (ESRI Redlands, CA). Cores were randomly assigned to either a training (75%) or validation set (25%). The training set was used to
model the relationships between soil color, landscape position, soil series, terrain attributes, and location. Separate relationships were developed for each land use. The validation set was used to test the prediction accuracy of each model. First, the samples of the training set were used to develop predictive equations between SOCC and soil color (see Chapter 3). Regression was done using SAS system for windows V9.1 software (SAS Institute, 1999). The predicted values of samples were used to calculate a total volume of carbon within 0.2m and 1.0m of the soil surface. These predicted values were used in conjunction with GIS and geostatistical prediction techniques.

The training cores were grouped by soil map unit and landscape position. Soil series polygons were obtained from the Iowa Cooperative Soil Survey (ICSS, 2003). Cores were grouped by location of soil map units and not by the morphology of individual cores. Landscape positions were identified at sample locations in the field using the summit, shoulder, backslope, footslope and toeslope model (Ruhe, 1975). Landscape position polygons were manually digitized using field classification, slope and curvature derived from DEMs using ArcGIS. In these models, the predicted SOCC at any given location is equal to the average SOC values of the class into which that location falls. In a second set of models, the soil color predicted SOCC of description cores were added to improve accuracy.

Digital elevation models (DEM) were developed from points gathered with a vehicle based real time kinematic global positioning system (RTK-GPS) in each land use. RTK-GPS uses differential-GPS with carrier phase ambiguity resolution to achieve horizontal accuracies of <1cm and vertical accuracies from 2 – 10 cm (CMT Z33 Operator’s Manual, 1997). A simple kriging procedure within ArcGIS was used to interpolate the elevation points to a 5m grid resolution. This DEM was used to calculate terrain attributes including
slope, curvature, and topographic wetness index (TWI) with the Terrain Analysis Programs for the Environmental Sciences – Grid version for windows (TAPES-G_win) within ArcGIS (ESRI, 2001). Topographic wetness index was calculated to quantify catenary landscape position on a 5m raster grid (Gessler et al., 2000). TWI = ln (As/tanB) where As is specific catchment area and B is the slope gradient in radians (Moore et al., 1993). See Gallant and Wilson (2000) and Wilson and Gallant (2000) for a more complete description of the TAPES-G calculations. Elevation, slope and TWI are shown for both land uses in Figure 2. Terrain attribute values were extracted for each core location. Stepwise regression was used to determine the best predictive relationships between SOCC and terrain variables using SAS 9.1 for Windows. Significance was considered at the 0.05 level.

Geostatistical analyses were done using the Geostatistical Analyst extension of ArcGIS. Various techniques were attempted to fit semi-variograms models to the soil properties at each grid point (Johnston et al, 2001). Secondary attributes of soil series, landscape positions, and elevation classes were used to attempt to improve predicted values (Goovaerts, 1999; Odeh et al., 1994). These semi-variogram functions were then used with ordinary kriging to predict property values on a 1m grid across each land use. A similar procedure was followed for co-kriging SOC contents with color values. Two sets of models were used to incorporate predicted SOCC by description and chroma meter color.

Finally, predictions using GIS classes, terrain attributes and geostatistical mapping were compared by prediction accuracy and land use averages. The accuracy of the model indicates the explanatory usefulness of each model to each property and land use. Regression coefficient of determination and root mean square prediction error (RMSE) were used to evaluate the accuracy of each prediction technique. Average SOCC prediction was
done by taking area weighted property means of each land use for each prediction strategy. For GIS analyses, the mean of each class was weighted by the area of that class. For terrain and geostatistical analyses, raster calculations use the value of each cell and cell size to produce a weighted average.

**Results and Discussion**

Soil color was used to predict soil organic carbon content (SOCC) on a weight per volume basis for individual samples of both the agricultural field and prairie. A weight per weight prediction, with and without log transformation, was also used for prairie description samples to improve $r^2$ values. These values were then converted to weight per volume using measured bulk density values. In the final analyses, there is generally no improvement between these alternate SOCC sample predictions by weight instead of volume (Table 2 and Figure 3). Therefore, the remainder of the results presented will be for predictions based on SOCC by volume measurements.

Predicting SOCC with soil color would allow rapid, low cost assessment of carbon stores across fields and landscapes. The relationship between SOCC and soil color was previously determined through a variety of measurements (Chapter 5). For this study, two of the best predictors of SOCC, chroma meter colors of depth increments and Munsell Soil Color Book colors of horizon matrix descriptions, were chosen for their contrasting technique and good fit. The combination of Munsell value, chroma, and the depth of measurement were regressed with the SOCC of each sample. The coefficients of determinations for these methods are given in Table 1. The $r^2$'s range from 0.74 – 0.07. These equations differ slightly from those given in Chapter 5 because only samples in the training set were used to develop these equations.
When SOCC predictions of individual samples are summed to depths of 0.2m and 1.0m the relationships between SOC and soil color are not as strong as they are with individual samples. In both land uses, only description color predictions to 0.2m were significantly related to SOCC measurements (Tables 2 and 3). These models predict a narrow range of values over the larger range of actual values (Figure 3). While it is possible that soil color in combination with other factors may be used to improve SOC predictions, soil color alone is not suitable for characterizing SOCC in these landscapes.

While previous studies have shown SOC to be related to terrain attributes (Gessler et al., 2001, Ventura and Irvin, 2000; Bell et al., 2000; Thompson and Bell, 1998; Odeh et al., 1994; Moore et al., 1991), we found only moderate correlations in the agricultural field and very little in the prairie. Previous studies often use one to a few sample locations to characterize a range or class of terrain attributes (Gessler et al., 2001, Thompson et al., 1998). By measuring more of the variability present in the landscape, we dilute the simplicity and parsimony of these relationships. However, the relationships we are able to obtain should have broader applicability.

The ranges of terrain attribute values for the prairie and agricultural field are given in Table 4. Elevation, slope, and TWI are shown for each land use in Figure 3. Stepwise regression of terrain attributes and SOCC indicated that only TWI was significant for the agricultural field and no attribute was significant for the prairie. For consistency and comparisons sake, regression was performed on both land uses and depths. Topographic wetness index, TWI, had the greatest $r^2$ values of any model for the agriculture field; however, it was not significant for the prairie for both 0.2m (0.52 versus 0.06) and 1.0m
(0.66 versus 0.12) (Table 3 and Figure 4). There were no improvements made to the terrain attribute models by including color predicted values for either land use.

The differing relationships between SOCC and terrain attributes are related to the overall distribution of SOC in each land use. The spatial distribution of SOCC is different in each land use due to the alteration of the agricultural field by tillage and artificial drainage (see Chapter 4). When visually analyzed by individual core, or ordinary kriging, mid-slope areas of the prairie, which have mid-TWI values, tend to have the greatest SOCC. Our best TWI regression equation still assumes a linear relationship, therefore SOCC predicted by TWI results in a different distribution of SOC than other methods.

Geostatistical analysis uses the relationship of both SOCC and soil color with location to enable prediction at un-sampled locations. Ordinary kriging was used to predict measured and color predicted SOCC across each land use individually. Despite numerous attempts at improving the model through reduction of least squares and visual fit, the spherical semi-variogram model with the default values of Geostatistical Wizard were found to be the best estimators in each case. Those semi-variograms were used to perform ordinary kriging which predicted SOCC on a regular grid across each land use.

Ordinary kriging of measured values was the best estimator of 0.2m SOCC in the prairie ($r^2 = 0.69$) (Table 1). The coefficient of determination was much lower for SOCC to 1.0m in both land uses (Table 3). Ordinary kriging of chroma meter predictions were significantly related to measured values in the prairie ($0.2m, r^2 = 0.29, 1.0m, r^2 = 0.24$). Ordinary kriging of description predictions did not produce a significant relationship for the 1.0m measurement in prairie and neither color prediction was significant for either depth in the agriculture field (Table 5 and Figure 4). Although ordinary kriging prediction and actual
training set values have a strong relationship (due to the nature of kriging), the validation set is not well predicted. The prediction of just validation cores is shown in Figure 5.

Co-kriging is useful when a cheaply, easily measured property, such as soil color, can be correlated to a more difficult and expensive to obtain property of interest, such as SOCC. Direct use of soil color for the prediction of SOCC to depths is difficult because their supports (or sample size underlying the measurement) are different. Soil color is measured on horizons or depth increment while SOCC is summed over the entire core to a depth of 0.2 and 1.0m. There is no standard way to sum or average color measurements over depth. Therefore, instead of actual color values, we used the SOCC value predicted with each color measurement technique to attempt to improve the accuracy of kriging prediction.

Co-kriging was done with SOCC predicted by chroma meter colors, measurements taken on depth increments, and description colors, measurements taken on horizon peds. Co-kriging of measured SOCC with chroma meter predicted values are significant for 1.0m ($r^2=0.25$) in the prairie, but co-kriging with description predictions are not. Neither technique produces a significant model in the agricultural field (Table 5). Co-kriging did smooth the raster prediction around individual measurements, particularly in the 1.0m SOCC prediction in the agricultural field (Figures 7).

In the analysis of GIS class models, the average of each class, soil series or landscape position, was used to predict the value of SOCC at all locations where that class is mapped. Regression of predicted soil series and landscape position SOCC with measured values in the validation set yielded generally poor results. Neither soil series map units nor landscape positions were a significant predictor of SOCC in either the agriculture field or the prairie (Table 3). Using classes also obscures some of the detail apparent in the raster predictions of
terrain attributes, ordinary kriging, and co-kriging (Figures 8 and 9). Color SOCC predictions were included in the average of GIS classes to increase the extent of measurement within each mapping unit. Soil series and landscape position averages were not significant predictors for any depth, land use, or color prediction combination (Table 5). Despite their use by other researchers to characterize SOCC, these models are not suitable for characterizing SOCC distributions on this landscape at this scale.

Comparison of Techniques

The most important aspect of a prediction strategy is the cumulative effect it will have on drawing scientific conclusions and making policy decisions. While none of these models were satisfactory for both depths and land uses, the overall range and mean of prediction is surprisingly similar. This indicates that they may be useful in ascertaining the average carbon contents of a given area, but are not suitable to evaluate the pattern of SOC content distribution across those areas. The ranges of predicted values are given for GIS classes, soil series and landscape position (Table 6), and raster predictions, TWI, ordinary kriging, and co-kriging (Table 7). The raster predictions have a much greater range because they are predicted on small grids, or rasters, instead of larger class polygons (Figures 6, 7, 8, and 9). This will likely be important when trying to characterize a site in some detail. To further compare prediction techniques, the SOCC range of values predicted at all core locations can be compared to the range in values for just those cores used in validation (Table 8 and 9). The validation data set covers nearly the same range as the entire core set with generally greater SE for each prediction strategy.

The models using only landscape position and measured SOCC values produce the greatest weighted average predictions in the agriculture field. Using only the measured
SOCC values in prediction, landscape position predicts a weighted average SOCC of 7.19 kg m\(^2\) to 0.2m while soil series predicts 6.45 kg m\(^2\) to 0.2m. Generally, the weighted averages using the same color data are similar with landscape positions being slightly greater. Raster prediction averages range from 5.26 kg m\(^2\) to 0.2m to 6.96 kg m\(^2\) to 0.2m and 12.08 kg m\(^2\) to 1.0m to 1438 kg m\(^2\) to 1.0m SOCC in the agriculture field. At both depths, the lowest average raster prediction value is from ordinary kriging with description color and the highest is for TWI. Overall, the agriculture predictions fall within a range of 2.40 kg m\(^2\) to 0.2m and 3.84 kg M\(^2\) to 1.0m.

In the prairie, the greatest GIS class SOCC prediction is from the landscape position-model at 0.2m (11.84 kg m\(^2\) to 0.2m) but soil series was greater at 1.0m (24.12 kg m\(^2\) to 1.0m). In the 0.2m prairie models, both soil series and landscape position models with color are lower than those using only measured value. Using color in these models would cause an under estimation of SOCC. The 1.0m models do not show this trend. Prairie raster predictions vary widely with the greatest prediction being for co-kriging with chroma meter 21.97 kg m\(^2\) to 0.2m and the lowest for ordinary kriging with description colors 6.26 kg m\(^2\) to 0.2m. At 1.0m depth, the range of SOCC from highest to lowest predictions is 24.20 kg m\(^2\) to 1.0m and 29.88 kg m\(^2\) to 1.0m. Over all techniques, average SOCC predictions vary by 6.18 kg m\(^2\) to 0.2m and 19.04 kg m\(^2\) to 1.0m from lowest to highest. These ranges are 2.5 times greater at 0.2m depth and 5 times greater than the range in predictions of the agriculture field.

**Conclusions**

Only a few models in this study were generally satisfactory for predicting SOCC across either the agricultural field or the prairie. Regression of measured values to predicted
values of the validation core set indicated that only a handful of models were significant. No one model did a good job of predicting SOCC across both depths and land uses. TWI was the best predictor for both depths in the agricultural field ($r^2 = 0.52$ and 0.66) while two other models best predicted SOCC in the prairie: ordinary kriging of measured values at 0.2m ($r^2=0.69$), and co-kriging with chroma meter colors at 1.0m ($r^2=0.25$). Ordinary kriging of chroma meter predictions was also significant at both depths in the prairie.

The rank of model average SOCC predictions and RMSE are not consistent between land uses or depths. In the agricultural field, ordinary kriging with description colors produced the largest prediction while landscape position produced the lowest. In the prairie, the highest and lowest value model depends upon the depth in question. Using the most accurate model in each land use for comparison, we can draw some conclusions about the relative estimation of SOCC from other models. In the agricultural field, the most accurate model (TWI) predicted SOCC content second from the highest in both depths. The most accurate models in the prairie produced the highest (0.2m) and second highest (0.1m) prediction values. This indicates that other models are generally underestimating the amount of SOCC in both land uses. Average land use SOCC predictions vary by 2.40 kg m$^{-2}$ to 0.2m and 3.84 kg m$^{-2}$ to 1.0m in the agriculture field and 6.18 kg m$^{-2}$ to 0.2m and 19.04 kg m$^{-2}$ to 1.0m in the prairie. These differences are significant and would be compounded if predictions were being extrapolating over larger areas. The model chosen will have considerable impact on research conclusions or management decisions made from SOCC predictions.
References


Table 1. Equations derived from regression of training set samples and used to predict soil organic carbon content for individual samples of all cores.

<table>
<thead>
<tr>
<th>Description</th>
<th>AG $, \text{kg m}^{-3}$</th>
<th>PR $, \text{kg m}^{-3}$</th>
<th>PR $, \text{g kg}^{-1}$</th>
<th>PR $, \log g , \text{kg}^{-1}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>45.52</td>
<td>26.32</td>
<td>4.77</td>
<td>2.07</td>
</tr>
<tr>
<td>mid-point $\dagger$</td>
<td>-0.21</td>
<td>-0.40</td>
<td>-0.009</td>
<td>-0.004</td>
</tr>
<tr>
<td>Value</td>
<td>-11.98</td>
<td>0.21</td>
<td>-0.48</td>
<td>-0.21</td>
</tr>
<tr>
<td>Chroma</td>
<td>16.53</td>
<td>10.64</td>
<td>-0.21</td>
<td>-0.09</td>
</tr>
<tr>
<td>$r^2$</td>
<td>0.74</td>
<td>0.47</td>
<td>0.46</td>
<td>0.70</td>
</tr>
</tbody>
</table>

$\dagger$ mid-point is the middle depth of the horizon or depth increment on which a color measurement was made.

$\ddagger$ AG, agricultural field; Pr, prairie.
Table 2. Soil organic carbon content models using soil color to predict soil organic carbon (SOC) and Log_{10} SOC of individual samples. SOC (kg m^{-2}) is calculated using sample bulk density and thickness.

<table>
<thead>
<tr>
<th>Model</th>
<th>Transformation</th>
<th>r^2</th>
<th>RMSE (0.2m)</th>
<th>r^2</th>
<th>RMSE (1.0m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Geostatistics †</td>
<td>None</td>
<td>0.0242</td>
<td>2.75</td>
<td>0.1549</td>
<td>4.75</td>
</tr>
<tr>
<td>Ordinary Kriging</td>
<td>Log</td>
<td>0.0134</td>
<td>2.77</td>
<td>0.2032</td>
<td>4.61</td>
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<tr>
<td>Co-kriging</td>
<td>None</td>
<td>0.0037</td>
<td>2.78</td>
<td>0.1403</td>
<td>4.79</td>
</tr>
<tr>
<td></td>
<td>Log</td>
<td>0.0131</td>
<td>2.77</td>
<td>0.1547</td>
<td>4.75</td>
</tr>
<tr>
<td>GIS Analysis §</td>
<td>None</td>
<td>0.1226</td>
<td>2.61</td>
<td>0.0939</td>
<td>4.92</td>
</tr>
<tr>
<td>Landscape Position</td>
<td>Log</td>
<td>0.0015</td>
<td>2.78</td>
<td>0.0558</td>
<td>5.02</td>
</tr>
<tr>
<td>Soil Series</td>
<td>None</td>
<td>0.1676</td>
<td>2.54</td>
<td>0.2315</td>
<td>4.53</td>
</tr>
<tr>
<td></td>
<td>Log</td>
<td>0.0266</td>
<td>2.75</td>
<td>0.2283</td>
<td>4.54</td>
</tr>
</tbody>
</table>

† R^2 and RMSE given for regression of model predicted and actual measurements of SOC kg m^{-2} of the validation set.
‡ Ordinary kriging used only soil organic carbon values predicted with color; co-kriging uses both measured and color predicted soil organic carbon values.
§ Landscape position and soil series models used both measured and color predicted soil organic carbon content.
Table 3. Coefficient of determination and root means square prediction error of model predictions and measured soil organic carbon content (kg m$^{-2}$) of the validation set.

<table>
<thead>
<tr>
<th>Model</th>
<th>Agriculture</th>
<th></th>
<th></th>
<th>Prairie</th>
<th></th>
<th></th>
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</thead>
<tbody>
<tr>
<td></td>
<td>$r^2$</td>
<td>RMSE</td>
<td>$r^2$</td>
<td>RMSE</td>
<td>$r^2$</td>
<td>RMSE</td>
</tr>
<tr>
<td></td>
<td>0.2m</td>
<td>1.0m</td>
<td>0.2m</td>
<td>1.0m</td>
<td>0.2m</td>
<td>1.0m</td>
</tr>
<tr>
<td>Chroma meter †</td>
<td>0.1044</td>
<td>1.18</td>
<td>0.0140</td>
<td>3.06</td>
<td>0.0550</td>
<td>2.82</td>
</tr>
<tr>
<td>Description§</td>
<td>0.2371*</td>
<td>1.09</td>
<td>0.0258</td>
<td>3.04</td>
<td>0.2572*</td>
<td>2.50</td>
</tr>
<tr>
<td>TWI</td>
<td>0.5202*</td>
<td>0.87</td>
<td>0.6629*</td>
<td>0.68</td>
<td>0.0642</td>
<td>2.81</td>
</tr>
<tr>
<td>Ordinary Kriging</td>
<td>0.2368</td>
<td>2.81</td>
<td>0.0318</td>
<td>1.14</td>
<td>0.6879*</td>
<td>1.56</td>
</tr>
<tr>
<td>Landscape Position</td>
<td>0.0428</td>
<td>1.22</td>
<td>0.1047</td>
<td>2.92</td>
<td>0.0396</td>
<td>2.84</td>
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<tr>
<td>Soil Series</td>
<td>0.0276</td>
<td>1.23</td>
<td>0.0127</td>
<td>3.06</td>
<td>0.0096</td>
<td>2.89</td>
</tr>
</tbody>
</table>

* significant at the 0.05 level
† RMSE, root mean square error; TWI, topographic wetness index.
‡ Chroma meter colors were taken at regular depth increments on split cores
§ Description colors are of horizon matrix using a Munsell color book.
Table 4. Range of terrain attributes in the agricultural field (a) and the prairie (b). †

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>SE ‡</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>a) agricultural field</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Elevation m</td>
<td>389.07</td>
<td>0.34</td>
<td>382.48</td>
<td>394.61</td>
</tr>
<tr>
<td>SLOPE %</td>
<td>3.53</td>
<td>0.12</td>
<td>0.94</td>
<td>5.49</td>
</tr>
<tr>
<td>SLOPE °</td>
<td>2.02</td>
<td>0.07</td>
<td>0.54</td>
<td>3.14</td>
</tr>
<tr>
<td>Curvature</td>
<td>0.01</td>
<td>0.03</td>
<td>-0.64</td>
<td>0.73</td>
</tr>
<tr>
<td>Profile</td>
<td>0.001</td>
<td>0.02</td>
<td>-0.31</td>
<td>0.57</td>
</tr>
<tr>
<td>Plan</td>
<td>0.01</td>
<td>0.02</td>
<td>-0.15</td>
<td>0.65</td>
</tr>
<tr>
<td>TWI</td>
<td>5.93</td>
<td>0.05</td>
<td>5.20</td>
<td>6.83</td>
</tr>
<tr>
<td>b) prairie</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Elevation m</td>
<td>392.17</td>
<td>0.47</td>
<td>386.95</td>
<td>399.70</td>
</tr>
<tr>
<td>SLOPE %</td>
<td>3.10</td>
<td>0.11</td>
<td>0.517</td>
<td>4.56</td>
</tr>
<tr>
<td>SLOPE °</td>
<td>1.77</td>
<td>0.06</td>
<td>0.30</td>
<td>2.61</td>
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<tr>
<td>Curvature</td>
<td>-0.02</td>
<td>0.07</td>
<td>-2.90</td>
<td>0.76</td>
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<td>-0.51</td>
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<td>Plan</td>
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<td>0.040</td>
<td>-1.45</td>
<td>0.80</td>
</tr>
<tr>
<td>TWI</td>
<td>6.56</td>
<td>0.08</td>
<td>5.27</td>
<td>8.54</td>
</tr>
</tbody>
</table>

† Terrain attributes derived from a digital elevation model with the TAPES-G extension of ArcGis, ArcMap (ESRI).
‡ SE, standard error; TWI, topographic wetness index.
Table 5. Coefficient of determination and root means square prediction error for model predictions and measured soil organic carbon content (kg m$^{-2}$) of the validation core set.

<table>
<thead>
<tr>
<th>Model</th>
<th>Color</th>
<th>Agriculture</th>
<th></th>
<th></th>
<th>Prairie</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>r$^2$</td>
<td>RMSE †</td>
<td>r$^2$</td>
<td>RMSE</td>
<td>r$^2$</td>
<td>RMSE</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.2m</td>
<td>1.0m</td>
<td>0.2m</td>
<td>1.0m</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ordinary kriging</td>
<td>Chroma meter</td>
<td>0.0017</td>
<td>1.15</td>
<td>0.0078</td>
<td>3.07</td>
<td>0.2943*</td>
<td>2.48</td>
</tr>
<tr>
<td>of color prediction ‡</td>
<td>Description</td>
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<td>1.09</td>
<td>0.0135</td>
<td>3.06</td>
<td>0.1825</td>
<td>2.67</td>
</tr>
<tr>
<td>Co-kriging</td>
<td>Chroma meter</td>
<td>0.0276</td>
<td>1.23</td>
<td>0.0857</td>
<td>2.95</td>
<td>0.1344</td>
<td>2.75</td>
</tr>
<tr>
<td></td>
<td>Description</td>
<td>0.0234</td>
<td>1.23</td>
<td>0.0965</td>
<td>2.93</td>
<td>0.1307</td>
<td>2.75</td>
</tr>
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<td>Chroma meter</td>
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<td>0.0737</td>
<td>2.9</td>
<td>0.0000</td>
<td>2.90</td>
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<td>0.0046</td>
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<tr>
<td>Soil Series</td>
<td>Chroma meter</td>
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<td>0.0000</td>
<td>3.08</td>
<td>0.0197</td>
<td>2.87</td>
</tr>
<tr>
<td></td>
<td>Description</td>
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<td>1.24</td>
<td>0.0091</td>
<td>3.07</td>
<td>0.0096</td>
<td>2.89</td>
</tr>
</tbody>
</table>

* significant at the 0.05 level
† RMSE, root mean square error; TWI, topographic wetness index.
‡ Chroma meter colors were taken at regular depth increments on split cores, description colors are of horizon matrix using Munsell Soil Color Book.
Table 6. Mean soil organic carbon contents (kg m$^{-2}$) of each land use using GIS class averages weighted by area.

<table>
<thead>
<tr>
<th>Model</th>
<th>Agriculture</th>
<th>Prairie</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Depth</td>
<td>Soil Series</td>
</tr>
<tr>
<td><strong>Measured</strong></td>
<td>kg m$^{-3}$</td>
<td>0.2m</td>
</tr>
<tr>
<td></td>
<td>kg m$^{-3}$</td>
<td>1.0m</td>
</tr>
<tr>
<td><strong>Description</strong></td>
<td>kg m$^{-3}$</td>
<td>0.2m</td>
</tr>
<tr>
<td></td>
<td>kg m$^{-3}$</td>
<td>1.0m</td>
</tr>
<tr>
<td><strong>Chroma meter</strong></td>
<td>kg m$^{-3}$</td>
<td>0.2m</td>
</tr>
<tr>
<td></td>
<td>kg m$^{-3}$</td>
<td>1.0m</td>
</tr>
<tr>
<td><strong>Description</strong></td>
<td>g kg$^{-1}$</td>
<td>0.2m</td>
</tr>
<tr>
<td></td>
<td>Log g kg$^{-1}$</td>
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</tr>
<tr>
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<td>g kg$^{-1}$</td>
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</tr>
<tr>
<td></td>
<td>Log g kg$^{-1}$</td>
<td>1.0m</td>
</tr>
</tbody>
</table>

† Measured predictions used only the values from soil organic carbon content measurement. Description and chroma meter values used color predictions in determining class mean.

‡ Description colors were used to predict soil organic carbon content on both a volume basis (kg m$^{-3}$) basis and weight (g kg$^{-1}$ and log g kg$^{-1}$) basis.

§ Chroma meter colors were taken at regular depth increments on split cores, description colors are of horizon matrix using a Munsell Soil Color Book.
Table 7. Mean and range of soil organic carbon content (kg m\(^{-2}\)) models predicted on a raster basis.

<table>
<thead>
<tr>
<th>Model</th>
<th>Depth</th>
<th>Agriculture</th>
<th></th>
<th>Prairie</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>min</td>
<td>max</td>
<td>mean</td>
<td>min</td>
</tr>
<tr>
<td>Ordinary Kriging</td>
<td>0.2m</td>
<td>4.88</td>
<td>8.00</td>
<td>6.61</td>
<td>7.44</td>
</tr>
<tr>
<td></td>
<td>1.0m</td>
<td>8.46</td>
<td>23.26</td>
<td>13.73</td>
<td>19.47</td>
</tr>
<tr>
<td>Ordinary Kriging*</td>
<td>0.2m</td>
<td>4.79</td>
<td>5.37</td>
<td>5.26</td>
<td>5.37</td>
</tr>
<tr>
<td></td>
<td>1.0m</td>
<td>9.11</td>
<td>16.73</td>
<td>12.08</td>
<td>20.38</td>
</tr>
<tr>
<td>Chroma meter</td>
<td>0.2m</td>
<td>5.66</td>
<td>8.58</td>
<td>6.76</td>
<td>7.67</td>
</tr>
<tr>
<td></td>
<td>1.0m</td>
<td>6.88</td>
<td>25.89</td>
<td>13.02</td>
<td>21.38</td>
</tr>
<tr>
<td>Co-kriging</td>
<td>0.2m</td>
<td>5.91</td>
<td>7.57</td>
<td>6.79</td>
<td>6.89</td>
</tr>
<tr>
<td></td>
<td>1.0m</td>
<td>11.13</td>
<td>18.62</td>
<td>14.00</td>
<td>17.73</td>
</tr>
<tr>
<td>Chroma meter</td>
<td>0.2m</td>
<td>5.75</td>
<td>7.73</td>
<td>6.80</td>
<td>6.92</td>
</tr>
<tr>
<td></td>
<td>1.0m</td>
<td>11.19</td>
<td>18.61</td>
<td>14.00</td>
<td>18.24</td>
</tr>
<tr>
<td>TWI</td>
<td>0.2m</td>
<td>5.36</td>
<td>10.40</td>
<td>6.96</td>
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</tr>
<tr>
<td></td>
<td>1.0m</td>
<td>9.84</td>
<td>24.13</td>
<td>14.38</td>
<td>22.42</td>
</tr>
</tbody>
</table>

* significant at the 0.05 level
† Min., minimum; Max., maximum; TWI, topographic wetness index.
‡ Chroma meter colors were taken at regular depth increments on split cores, description colors are of horizon matrix using a Munsell Soil Color Book.
Table 8. Range and mean of measured and predicted soil organic carbon content (kg m$^{-2}$) for all cores and just those used in model validation in the agriculture field.

<table>
<thead>
<tr>
<th>Model</th>
<th>Depth</th>
<th>Mean</th>
<th>SE†</th>
<th>Min.</th>
<th>Max.</th>
<th>Mean</th>
<th>SE</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Measured</td>
<td>0.2m</td>
<td>6.66</td>
<td>0.17</td>
<td>3.07</td>
<td>10.61</td>
<td>6.25</td>
<td>0.29</td>
<td>4.17</td>
<td>8.40</td>
</tr>
<tr>
<td></td>
<td>1.0m</td>
<td>13.84</td>
<td>0.40</td>
<td>8.37</td>
<td>2.34</td>
<td>13.56</td>
<td>0.72</td>
<td>8.77</td>
<td>21.33</td>
</tr>
<tr>
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<td>0.03</td>
<td>3.20</td>
<td>6.11</td>
<td>5.06</td>
<td>0.14</td>
<td>3.47</td>
<td>5.33</td>
</tr>
<tr>
<td></td>
<td>1.0m</td>
<td>12.20</td>
<td>0.18</td>
<td>6.80</td>
<td>21.65</td>
<td>12.78</td>
<td>0.61</td>
<td>8.66</td>
<td>18.80</td>
</tr>
<tr>
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<td>3.79</td>
<td>19.87</td>
<td>6.89</td>
<td>0.22</td>
<td>5.61</td>
<td>8.16</td>
</tr>
<tr>
<td></td>
<td>1.0m</td>
<td>12.99</td>
<td>0.61</td>
<td>2.18</td>
<td>47.35</td>
<td>13.69</td>
<td>2.27</td>
<td>3.98</td>
<td>33.78</td>
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<td>0.07</td>
<td>5.23</td>
<td>8.34</td>
<td>6.81</td>
<td>0.17</td>
<td>5.23</td>
<td>8.34</td>
</tr>
<tr>
<td></td>
<td>1.0m</td>
<td>13.34</td>
<td>0.18</td>
<td>10.26</td>
<td>18.25</td>
<td>14.54</td>
<td>0.46</td>
<td>10.26</td>
<td>18.25</td>
</tr>
<tr>
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<td>0.05</td>
<td>5.16</td>
<td>7.60</td>
<td>6.38</td>
<td>0.12</td>
<td>5.16</td>
<td>7.59</td>
</tr>
<tr>
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<td>1.0m</td>
<td>13.43</td>
<td>0.11</td>
<td>11.31</td>
<td>16.46</td>
<td>13.06</td>
<td>0.23</td>
<td>11.31</td>
<td>16.46</td>
</tr>
<tr>
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<td>6.54</td>
<td>0.04</td>
<td>4.88</td>
<td>8.00</td>
<td>6.60</td>
<td>0.13</td>
<td>5.16</td>
<td>7.35</td>
</tr>
<tr>
<td></td>
<td>1.0m</td>
<td>13.16</td>
<td>0.14</td>
<td>8.46</td>
<td>22.05</td>
<td>13.60</td>
<td>0.71</td>
<td>8.92</td>
<td>21.25</td>
</tr>
<tr>
<td>Co-kriging:</td>
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<td>7.51</td>
<td>6.94</td>
<td>0.07</td>
<td>6.26</td>
<td>7.44</td>
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<tr>
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<td>11.16</td>
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<td>14.75</td>
<td>0.22</td>
<td>12.98</td>
<td>17.20</td>
</tr>
<tr>
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<td>5.52</td>
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<td>0.08</td>
<td>6.37</td>
<td>7.45</td>
</tr>
<tr>
<td>chroma meter</td>
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<td>0.36</td>
<td>6.57</td>
<td>27.14</td>
<td>11.64</td>
<td>0.72</td>
<td>8.76</td>
<td>17.44</td>
</tr>
<tr>
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<td>3.40</td>
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<td>6.73</td>
<td>0.09</td>
<td>5.93</td>
<td>7.29</td>
</tr>
<tr>
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<td>1.0m</td>
<td>13.71</td>
<td>0.10</td>
<td>9.64</td>
<td>18.04</td>
<td>13.72</td>
<td>0.27</td>
<td>11.45</td>
<td>15.30</td>
</tr>
</tbody>
</table>

† SE, standard error; Min., minimum; Max., maximum; TWI, topographic wetness index.  
‡ Chroma meter colors were taken at regular depth increments on split cores, description colors are of horizon matrix using a Munsell color book.
Table 9. Range and mean of measured and predicted soil organic carbon content (kg m$^{-2}$) for all cores and just those used in model validation in the prairie.

<table>
<thead>
<tr>
<th>Model</th>
<th>Depth</th>
<th>Mean</th>
<th>SE†</th>
<th>Min.</th>
<th>Max.</th>
<th>Mean</th>
<th>SE</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
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<td>0.42</td>
<td>5.80</td>
<td>23.94</td>
<td>11.56</td>
<td>0.68</td>
<td>6.99</td>
<td>16.72</td>
</tr>
<tr>
<td></td>
<td>1.0m</td>
<td>24.62</td>
<td>0.74</td>
<td>11.73</td>
<td>43.75</td>
<td>24.57</td>
<td>1.19</td>
<td>13.38</td>
<td>31.47</td>
</tr>
<tr>
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<td>4.81</td>
<td>7.25</td>
<td>6.20</td>
<td>0.06</td>
<td>6.10</td>
<td>7.19</td>
</tr>
<tr>
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<td>0.58</td>
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<td>71.17</td>
<td>26.60</td>
<td>1.38</td>
<td>18.02</td>
<td>43.94</td>
</tr>
<tr>
<td>Chroma meter</td>
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<td>8.28</td>
<td>0.06</td>
<td>4.36</td>
<td>16.96</td>
<td>8.15</td>
<td>0.09</td>
<td>4.36</td>
<td>8.98</td>
</tr>
<tr>
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<td>1.0m</td>
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<td>23.51</td>
<td>0.86</td>
<td>1.39</td>
<td>40.42</td>
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<td>0.12</td>
<td>8.87</td>
<td>15.76</td>
<td>11.44</td>
<td>0.71</td>
<td>6.99</td>
<td>16.72</td>
</tr>
<tr>
<td></td>
<td>1.0m</td>
<td>23.81</td>
<td>0.17</td>
<td>20.56</td>
<td>30.22</td>
<td>24.46</td>
<td>1.26</td>
<td>13.38</td>
<td>31.47</td>
</tr>
<tr>
<td>Landscape Position</td>
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<td>11.92</td>
<td>0.02</td>
<td>11.45</td>
<td>13.40</td>
<td>11.87</td>
<td>0.11</td>
<td>11.45</td>
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<td>0.25</td>
<td>23.57</td>
<td>27.24</td>
</tr>
<tr>
<td>Ordinary Kriging</td>
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<td>12.22</td>
<td>0.10</td>
<td>8.53</td>
<td>16.00</td>
<td>11.39</td>
<td>0.30</td>
<td>9.56</td>
<td>13.90</td>
</tr>
<tr>
<td></td>
<td>1.0m</td>
<td>26.24</td>
<td>0.16</td>
<td>21.99</td>
<td>30.18</td>
<td>24.42</td>
<td>0.53</td>
<td>21.99</td>
<td>29.65</td>
</tr>
<tr>
<td>Co-kriging: description</td>
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<td>12.27</td>
<td>0.12</td>
<td>8.06</td>
<td>16.04</td>
<td>11.13</td>
<td>0.35</td>
<td>8.34</td>
<td>14.72</td>
</tr>
<tr>
<td></td>
<td>1.0m</td>
<td>25.89</td>
<td>0.17</td>
<td>21.49</td>
<td>30.10</td>
<td>23.78</td>
<td>0.50</td>
<td>21.49</td>
<td>28.61</td>
</tr>
<tr>
<td>Co-kriging: chroma meter</td>
<td>0.2m</td>
<td>12.24</td>
<td>0.13</td>
<td>8.04</td>
<td>16.06</td>
<td>11.10</td>
<td>0.37</td>
<td>8.24</td>
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</tr>
<tr>
<td></td>
<td>1.0m</td>
<td>25.66</td>
<td>0.19</td>
<td>20.20</td>
<td>29.59</td>
<td>23.61</td>
<td>0.52</td>
<td>20.92</td>
<td>28.54</td>
</tr>
<tr>
<td>TWI</td>
<td>0.2m</td>
<td>12.03</td>
<td>0.03</td>
<td>11.36</td>
<td>13.35</td>
<td>11.90</td>
<td>0.07</td>
<td>11.66</td>
<td>12.67</td>
</tr>
<tr>
<td></td>
<td>1.0m</td>
<td>24.64</td>
<td>0.06</td>
<td>23.00</td>
<td>27.89</td>
<td>24.34</td>
<td>0.18</td>
<td>23.73</td>
<td>26.24</td>
</tr>
</tbody>
</table>

† SE, standard error; TWI, topographic wetness index.
‡ Description colors are of horizon matrix using a Munsell Soil Color Book, chroma meter colors were taken at regular depth increments on split cores.
Figure 1. Location of study site on the Iowan Surface in northeastern Iowa, USA. Locations of training and validation cores are shown on an aerial photograph.
Figure 2. Digital elevation model, percent slope and topographic wetness index derived from RTK-GPS data analyzed with Geostatistical Wizard and TAPES-G extensions of ArcGIS.
Figure 3. Soil organic carbon content (kg m\(^{-2}\)) to 0.2m depth predicted by color for the agriculture field (a) and the prairie (b). Description predictions made with full horizon description model, Munsell value, chroma and horizon depth. Chroma meter predictions uses chroma meter Munsell value, chroma, and increment depth from the midpoint of predetermined depth increments.
Figure 4. Soil organic carbon content (kg m\(^{-2}\)) predicted by ordinary kriging, topographic wetness index (TWI) and soil series for all cores (training and validation sets).
Figure 5. Ordinary kriging prediction versus measured soil organic carbon content (kg m\(^{-2}\)) to 0.2m depth values for validation set cores only.
Figure 6. Soil organic carbon content (kg m$^{-2}$) predictions to a depth of 0.2m using ordinary kriging of measured SOC and co-kriging with measured SOC and SOC predicted with description colors and chroma meter colors. Description predictions made with full horizon description model, Munsell value, chroma and horizon depth. Chroma meter predictions use chroma meter Munsell value, chroma, and increment depth from the midpoint of predetermined depth increments.
Figure 7. Soil organic carbon (SOC) content (kg m$^{-2}$) predictions to a depth of 1.0m using ordinary kriging of measured SOC and co-kriging with measured SOC and SOC predicted with description colors and chroma meter colors. Description predictions were made with full horizon description model, Munsell value, chroma and horizon depth. Chroma meter predictions use chroma meter Munsell value, chroma, and increment depth from the midpoint of predetermined depth increments.
Figure 8. Soil organic carbon content (kg m\(^{-2}\)) predictions to a depth of 0.2m using GIS classes of soil series and landscape positions.
Figure 9. Soil organic carbon content (kg m$^{-2}$) predictions to a depth of 1.0m using GIS classes of soil series and landscape positions.
CHAPTER 7. GENERAL CONCLUSIONS

Summary

The impact of human land use on this landscape has been considerable. On average, the agriculture field and the prairie differ significantly in nearly all measured soil properties. Epipedon thickness, bulk density, soil organic carbon (SOC) content and water stable aggregate (WSA) content have the greatest differences. The greater average epipedon thickness of the prairie (47.9 cm versus 39.7 in the agricultural field) reflects the increased oxidation and erosion of surface materials that often occur with cultivation. These same factors also influence bulk density and soil organic carbon (SOC) content. Surface horizon bulk density is significantly greater in the agricultural field (1.26 g cm\(^{-3}\)) than the prairie (1.19 g cm\(^{-3}\)). Prairie epipedons have significantly greater SOC content than the agriculture field by 11.3 g kg\(^{-1}\), 2.5 kg m\(^{-3}\). Cultivation has also reduced soil aggregate stability, with the prairie having 36% more water stable aggregates.

Particle size distribution and pH differences, while still statistically significant, were much less dramatic. The pH of the agricultural field epipedon (5.9 pH) is slightly but significantly greater than the prairie (5.2 pH). Across all analyzed core surface horizons, the prairie has 4.2% greater coarse silt content and 2% less fine sand with no other fractions differing by more than 1.5%. For epipedons, the agriculture field has 7% greater total sand content, while the prairie has 3% more clay.
The Effect of Land Use on the Distribution of Soil Properties

Using GIS classes, the prairie has more stratification of soil properties between these soil classes. Soil series map units partitioned more properties into significantly different classes than landscape positions did. Soil series were significantly different within both land uses for epipedon thickness. Several particle size fractions and SOC content were significantly different within the prairie. Landscape positions were only significantly different for epipedon thickness in the agriculture field and prairie, and pH in the prairie. Particle size differences between soil series are more often significant in the prairie than the agricultural field. The greater number of significant differences between classes within the prairie indicates that its soil properties are generally more ordered than the agricultural field. I think this reflects the homogenization of agriculture soil properties through cultivation.

Geostatistical models indicate that the agricultural field has greater spatial dependence, as measured by nugget:sill ratio, than the prairie. While epipedon thickness was significantly different for soil series and landscape position within and between land uses, the semi-variogram model indicates that epipedon thickness is spatially dependent only in the agricultural field. SOC measurements were found to be spatially dependent in the agriculture field but not in the prairie. In contrast to SOC, nearly all particle size fractions were found to be spatially dependent with geostatistics for both land uses. This indicates that the spatiality of SOC has been influenced by land use while particle size distribution has not.

In a cursory evaluation, these models appear to give contradictory results. GIS models indicate that soil properties, particularly SOC and particle size fractions, are more spatially ordered in the prairie than the agricultural field. Geostatistical analysis indicates that SOC contents and particle size fractions are more spatially dependent in the agriculture
field. The lack of spatial dependence in the geostatistical model does not indicate a random
distribution of SOC across the prairie, but some combination of increased fine scale
variability and spatial dependence that cannot be adequately described given the constraints
of our sampling scheme and spatial model. The lack of these patterns in the agriculture field
is due, at least in part, to the homogenization of the soil moisture regime in the agriculture
field by tile drainage.

In the agricultural field, the highest SOC values are associated with the lowest
elevations while the highest prairie SOC values occur at mid-elevations. The high SOC,
mid-elevation areas of the prairie have poorly and somewhat poorly drained soils. While the
features used to define these drainage classes, i.e. gleyed subsoils and redoximorphic
features, are still present at mid-elevations in the agricultural field, these are most likely relict
features that do not reflect the current moisture regime under artificial drainage (James and
Fenton, 1993). Standing water and hydrophilic plants were noted in these areas of the prairie
at the time of sampling. However, “poorly” drained soils in the agriculture field (sampled
while water was standing in the prairie) had moisture contents of 10 – 30%. The spatial
distribution of soil forming and SOC controlling conditions has been altered by agricultural
drainage.

The homogenization of the agricultural field across the larger scales modeled in GIS
classes, does not necessarily contradict the fine scale spatial dependence indicated by very
low nuggets of particle size fractions in the geostatistical model. When examining the
distribution of organic matter and cation exchange capacity, Paz-González et al. (2000)
found that while cultivated soils were more homogeneous, they also had increased small
scale continuity (reducing nugget effects). The agriculture field has not been homogenized
to the point that property means are identical, or nearly so, but has been “smoothed” such that there are no large differences at small scales.

**Prediction of SOC with GIS and Geostatistical Models**

Only a few models in this study were generally satisfactory for predicting SOC content across either the agricultural field or the prairie. Soil color was tested as a simple, easy to measure proxy for SOC content. When soil color is used to predict SOC on individual samples, horizons, or depth increments, there are strong relationships. Soil color measurements were taken on split cores, horizon peds, and prepared, ground < 2mm, samples. These were done with a chroma meter on prepared samples, chroma meter and Munsell Soil Color book on split-cores at horizon and depth increment midpoints, and descriptions of horizon matrix. The best predictors of SOC were horizon descriptions for SOC by weight (g kg\(^{-1}\)) horizon midpoints, with Munsell color book, for SOC by volume (kg m\(^{-3}\)), and both chroma meter and Munsell Color Book measurements at depth increment midpoints for log transformed SOC by weight and volume. This indicates that SOC content predictions could be made on field measurements, by soil scientists using traditional survey methods or trained workers using the split-core technique, without laboratory analysis of all samples. However, when these techniques are applied to spatial predictions of SOC with depth, the predictions are not accurate.

GIS class predictions did a poor job of predicting SOC for both land uses. The map units of soil series and landscape analysis are too large and encompass disparate areas within their boundaries. However, terrain analysis proved useful for the agricultural field. Topographic wetness index was the best predictor for both the 0.2m and 1.0m depths in the agriculture field, but not in the prairie. This can be related to the different distributions of
SOC contents relative to elevation found in the GIS and geostatistical analyses. While I found that SOC was indeed related to wetness in the prairie, the greatest SOC contents in the prairie occur at mid-elevation and mid-TWI values. The TWI is not capturing the complex hydrology of the area with its simplistic calculation, using only up-slope area and slope. Geostatistical analysis included ordinary kriging and co-kriging with SOC predicted from color values. In the prairie, ordinary kriging of measured values at 0.2m and co-kriging with chroma meter colors at 1.0m depth were the best predictors of SOC. Geostatistical techniques did not do well in SOC content prediction in the agriculture field.

There was no consistent rank of prediction models in accuracy or prediction amounts. Average land use SOC content predictions vary by 2.40 kg m\(^{-2}\) to 0.2m depth and 3.84 kg m\(^{-2}\) to 1.0m depth in the agriculture field and 6.18 kg m\(^{-2}\) to 0.2m and 19.04 kg m\(^{-2}\) to 1.0m in the prairie. These differences are considerable and would be compounded if predictions were being extrapolating over larger areas. This study does not indicate the tendencies of individual models to fall at either end of these ranges. The model chosen will have considerable impact on research conclusions or management decisions made from SOC predications.

The most obvious answer for improving prediction of SOC is to take more samples. This runs counter to our original purpose of finding a cheap, easy method of predicting SOC content. Contrasting the analysis of all cores and laboratory analyzed cores indicates that the selection of the nested grid had significant impacts on our modeling and predictions conclusions. Changing the selection of the nested grid samples for laboratory analyses could certainly give us more data about finer scales across various parts of the landscape, but would it change our predictions?
Interestingly, and somewhat counter intuitively, the relationship between terrain attributes might have improved if we had taken fewer samples. A better relationship might also exist for fewer samples along taken on a transect and/or targeted to represent distinct terrain attributes or landscape positions (Gessler et al., 2001; Thompson et al., 1998). Although we would actually have less information, the information would appear to be more powerful. In this case, while we might have done a better job of modeling what we know (the samples we took), our model would have less applicability to predicting what we don’t know (unsampled locations).

**Implications**

This study was successful in evaluating the spatial distribution of soil properties, moderately successful in comparing land uses, somewhat successful at predicting sample SOC contents, and negligibly successful at predicting SOC with depth across the landscape. The more classical approach of soil series maps and landscape positions captured a significant portion of the variability in these landscapes. Geostatistical analysis (and the grid sampling it entailed) added detail to our knowledge of soil property distributions and improved SOC content predictions. The combination of these techniques (through targeted nested grid location) might allow us to further improve our knowledge and prediction of soil properties across these landscapes.

These models have conveyed the differences in spatiality between these land uses. They have highlighted the importance of agricultural drainage in changing SOC distributions. The biggest obstacle to conveying these differences with disparate models is the language used to discuss spatiality, or more specifically, spatial dependence. SOC, for instance, was shown to be more spatially stratified in the prairie with GIS while geostatistics
indicated less spatial dependence. The language used appears to put them at odds to one another.

Overall, I can conclude that SOC is more homogeneous in the agriculture field. However, I can also conclude that SOC is spatially dependent in the agricultural field but not in the prairie. This is not to say that I think SOC has no spatial pattern. It does differ spatially (different locations have different values) and there is order to the distribution (apparent from visual inspection and soil series map unit differences). Our simple geostatistical definition of spatial dependence (small nugget:sill ratios) is inadequate to describe this complex landscape. In the future, the concept of spatial dependence must be expanded and refined so that communication of these concepts will be improved.

The increased homogeneity of the agriculture field can also be thought of as the loss of soil heterogeneity in the prairie. This heterogeneity is a measure of the greater pedodiversity in Hayden Prairie (Ibanez et al., 1995; McBratney, 1995). These undisturbed soils have been called endangered by Amundson (2003). Some properties of the agriculture field are relicts (e.g. they do not reflect current conditions). The prairie gives us a link to the conditions that formed these soils. In her campaign to create prairie preserves in Iowa "..as a cathedral, a monument to the past", Dr. Ada Hayden expounded the virtues and importance of soils for preserving biodiversity and native soil conditions "..save the characteristic landscape, wild flower, and wildlife of the native prairies...and to the landscape belongs the soil (Hayden, 1944)." This study illustrates the importance of maintaining preserved areas that can serve as a benchmark for understanding soils and the landscapes to which they belong.
References


Hayden, A. 1944. Notes on Preservation of Prairies. Special Collections Department. Iowa State University Library.


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