Characterizing Subsurface Textural Properties Using Electromagnetic Induction Mapping and Geostatistics

Hiruy Abdu

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CHARACTERIZING SUBSURFACE TEXTURAL PROPERTIES USING ELECTROMAGNETIC INDUCTION MAPPING AND GEOSTATISTICS

by

Hiruy Abdu

A dissertation submitted in partial fulfillment of the requirements for the degree of DOCTOR OF PHILOSOPHY in Irrigation Engineering

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2009
ABSTRACT

Characterizing Subsurface Textural Properties Using Electromagnetic Induction Mapping and Geostatistics

by

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Utah State University, 2009

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Knowledge of the spatial distribution of soil textural properties at the watershed scale is important for understanding spatial patterns of water movement, and in determining soil moisture storage and soil hydraulic transport properties. Capturing the heterogeneous nature of the subsurface without exhaustive and costly sampling presents a significant challenge. Soil scientists and geologists have adapted geophysical methods that measure a surrogate property related to the vital underlying process. Apparent electrical conductivity (ECa) is such a proxy, providing a measure of charge mobility due to application of an electric field, and is highly correlated to the electrical conductivity of the soil solution, clay percentage, and water content. Electromagnetic induction (EMI) provides the possibility of obtaining high resolution images of ECa across a landscape to identify subtle changes in subsurface properties. The aim of this study was to better characterize subsurface textural properties using EMI mapping and geostatistical analysis
techniques. The effect of variable temperature environments on EMI instrumental response, and ECₐ – depth relationship were first determined. Then a procedure of repeated EMI mapping at varying soil water content was developed and integrated with temporal stability analysis to capture the time invariant properties of spatial soil texture on an agricultural field. In addition, an EMI imaging approach of densely sampling the subsurface of the Reynolds Mountain East watershed was presented using kriging to interpolate, and Sequential Gaussian Simulation to estimate the uncertainty in the maps. Due to the relative time-invariant characteristics of textural properties, it was possible to correlate clay samples collected over three seasons to ECₐ data of one mapping event. Kriging methods [ordinary kriging (OK), cokriging (CK), and regression kriging (RK)] were then used to integrate various levels of information (clay percentage, ECₐ, and spatial location) to produce clay percentage prediction maps. Leave-one-out cross-validation showed that the multivariate estimation methods CK and RK, incorporating the better sampled surrogate ECₐ, were able to improve the RMSE by 7% and 28%, respectively, relative to OK. Electromagnetic induction measurements provide an important exhaustive layer of information that can improve the quality and resolution of soil property maps used in hydrological and environmental research.
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CHAPTER 1
INTRODUCTION

The spatial distribution of subsurface soil textural properties across the landscape is an important control on the hydrological and ecological function of a watershed. However, the quantitative determination of the spatial properties of soils at the field or watershed scale remains a research challenge. Traditional methods of mapping soils involving subjective assignment of soil boundaries are inadequate for studies requiring a quantitative assessment of the landscape and its subsurface connectivity and storage capacity. The development of precision agriculture with the targeted application of fertilizer or irrigation could be further enhanced with improved, quantitative, soil textural data at the field scale.

Soils can be visualized as open systems reacting to processes that add and take away material and energy at their boundaries. The characteristics of soils can be attributed to the mixture of organic and mineral components, pores filled with water or air and the physical and chemical properties of the constituents (Gerrard, 2000). Near-subsurface physical properties can be divided into static intrinsic properties that are unaffected by external variables, and dynamic properties due to the response of the system to fluid and energy fluxes (Hillel, 1998). Some of the major dynamic properties are soil moisture, soil temperature, and soil gas concentration; while the static properties consist of soil texture, particle-size distribution, and specific surface area. The
abovementioned static properties determine the soil’s internal geometry and porosity, its interactions with fluids and solutes, and its thermal regime (Hillel, 1998).

These time-invariant static properties have a direct influence on the nature of the dynamic soil properties. The most important dynamic soil property affected by the time-invariant static soil physical properties is soil water content. Soil water status is critical to plant growth, crop quality, chemical fate and transport, and microbial processes. Soil structure and texture are important properties controlling the hydraulic conductivity and infiltration capacity of a soil system. These two properties in turn determine how much water is stored in a soil system as well as how much water is diverted from the system due to runoff. Soil water content is an important factor both for maintaining optimal plant growth and for many agricultural practices such as the timing of tillage or fertilizer application (Hillel, 1998). More importantly in dry climates, knowledge of the soil water content can reduce water waste and increase efficient use of this precious resource by scheduling irrigation more effectively. The micro distribution of water in the soil due to texture and mineralogy controls the fate of chemicals and micro-fauna making it important in reclamation studies. Thus efficient use of our soil and water resources mandates that knowledge of these and other soil physical properties be readily available to researchers and practitioners.

Presently, discrete point locations are chosen to sample soil physical and chemical properties in order to determine the coverage of soil types and regions. Thus soil regional maps are dependent on the original scheme of sampling which in turn is dependent on vegetation coverage, topography, and geological features. While this might be sufficient
to classify large areas, it is biased towards grouping and overlooks small scale soil variability. Our understanding of the distribution of subsurface physical properties is also limited by the sparse sampling plan and consequent interpolation method. Mindful of these shortcomings, we set out to advance electromagnetic measurement techniques as well as geostatistical estimation methods to create spatial images of subsurface properties.

Electromagnetic measurement methods make an important contribution to our ability to determine soil physical properties from the sample scale through the field/site scale to watershed scales. Although the support volume is restricted (making it costly to instrument larger areas), time domain reflectometry (TDR) provides reasonably reliable measurements. Unlike TDR, remote sensing can cover large areas but is limited to sensing the top few centimeters by its depth of penetration. Geophysical instruments are becoming more and more useful since they can measure soil physical properties of larger areas and suitable depths bridging measurement methods for intermediate scales between those of a point and remote sensing.

Soil scientists and geologists have adapted geophysical tools to study the near subsurface. These geophysical methods measure a surrogate property which is related to the vital underlying property (Hendrickx and Kachanoski, 2002). The apparent electrical conductivity ($EC_a$) is such a proxy, providing a measure of charge mobility due to application of an electric field, and is defined as the ratio between current density and electrical field. Several physical and chemical soil properties influence field scale $EC_a$ measurements. Friedman (2005) conveniently partitions the major factors into three
categories: bulk soil, solid particle and soil solution. The bulk soil category comprises the factors that are defined by the organization of a three phase soil system such as porosity \((n)\) and water content \((\theta)\); factors in the solid particle category include particle shape and orientation, particle-size distribution, cation exchange capacity (CEC), and wettability; ionic strength \((\sigma_w)\), cation composition and temperature are factors that are classified under the soil solution category.

Some methods of measuring apparent electrical conductivity include four-electrode sensors, electro-magnetic induction (EMI) sensors and TDR sensors (Rhoades et al., 1999). While the four-electrode and EMI sensors have been successfully adapted for mobile applications, the TDR sensor is still limited in its volume of measurement and mobility.

EMI instruments are gaining wider use due to their non-destructive nature, rapid response and ease of integration into a mobile platform, from which real-time measurements can be made (Hendrickx and Kachanoski, 2002; McNeill, 1980). The basic mechanism of EMI instruments is explained by Faraday's Law of electromagnetic induction (Eq. 1), which states that the voltage \((E)\) induced along a conductive material of perimeter \(C\) in the subsurface is proportional to the time rate-of-change of the magnetic flux \((B)\) penetrating the surface \(S\) whose perimeter is the contour \(C\) (Paul, 2004),

\[
\oint_{C} E \cdot dl = -\frac{d}{dt} \int_{S} B \cdot ds \quad [1]
\]
An electromagnetic induction instrument transmits a low frequency (lower KHz) electromagnetic field into the subsurface, whereby it induces current loops in proportion to the subsurface EC\textsubscript{a}. The current loops in turn induce secondary magnetic fields which are picked up by the receiver of the instrument, the ratio of the primary and secondary magnetic fields allows the determination of the soil EC\textsubscript{a}.

The non-invasive measuring characteristics of EMI instruments along with geographic positioning system (GPS) technology make field-scale geo-referenced EC\textsubscript{a} maps plausible (Corwin and Lesch, 2005). Once point measurements are obtained, we can apply geostatistical techniques to: i) characterize and interpret the spatial behavior of the variable of interest (e.g., soil texture) from the sampled data; ii) use the above interpretation to predict the likely values of the variable at locations which have not yet been sampled; and iii) quantify the uncertainty of our prediction at unsampled locations (Goovaerts, 1999). Continuously varying spatial variables such as EC\textsubscript{a} and subsurface physical properties (e.g. clay percentage) are good candidates for applying geostatistical methods since they exhibit an underlying spatial structure, i.e. observations close to each other are more alike than those further apart (Goovaerts, 1997).

The application of geostatistics to analyze data requires that each measured property is modeled as a random variable, thus making a methodological choice of using probabilistic (random) models (Goovaerts, 1999). Randomness does not imply that the phenomenon under study is stochastic; it only applies to the model we choose to describe and interpret the phenomenon to be able to estimate the variable at unsampled locations. In our case the EMI response, i.e. movement of electrical currents in the subsurface, can
not be sufficiently explained with deterministic models due to the complexity (heterogeneity) of the subsurface. Some deterministic models such as the parallel conductance electrical conductivity model (Rhoades et al., 1999) require about eight calibration variables for each measured EC$_a$ value. This complexity makes it hard to implement such deterministic models in heterogeneous field-scale sites and may only accurately model EC$_a$ in laboratory-controlled homogenous soil columns. Therefore it is advantageous to utilize a stochastic model to describe the distribution of EC$_a$ and related textural properties.

When dealing with unique phenomenon, such as EC$_a$, there is little possibility of repetition. Geostatistical estimation is only possible by accepting in one form or another, a hypothesis of at least local statistical homogeneity (Matheron, 1989). This stationary hypothesis will allow replacing repeatability in time, which is not available, by repetition in space. The phenomenon is expected to behave, where it is not known, in a manner reasonably analogous to the available data observed in close proximity. Multivariate kriging methods will improve the quality of estimation by making use of the cross-correlation between related variables, EC$_a$ and soil texture in this case.

**OBJECTIVES**

The aim of this study was to better characterize subsurface textural properties using electromagnetic induction (EMI) mapping and geostatistical analysis techniques. In order to accomplish this goal, the following objectives were implemented:
1. Evaluated EC<sub>a</sub>-depth relationship and the effect of thermal instability on the response of EMI instruments in soils with low and high electrical conductivity.

2. Developed a procedure to non-invasively derive time invariant field-scale soil textural patterns using repeated EMI mapping at varying soil water content.

3. Combined EMI mapping with geostatistical techniques to obtain high resolution images (with prediction uncertainty) across a small watershed to identify subtle changes in subsurface soil patterns and explored the idea of ‘difference EC<sub>a</sub> mapping’ to identify more hydrologically active locations.

4. Evaluated the use of EMI maps as surrogate variables to better predict soil texture at unsampled locations using multivariate kriging methods that integrated different levels of information such as clay percentage, apparent electrical conductivity (EC<sub>a</sub>), and spatial location.

To accomplish objective one the apparent soil electrical conductivity (EC<sub>a</sub>) – depth relationship between the DUALEM-1S and Geonics EM38-DD EMI instruments was compared and the effect of variable temperature environments on instrument response was determined. The relationship of EC<sub>a</sub> to the depth below ground was investigated by raising each instrument in increments of 0.15 m up to 1.8 m above ground. The effect of temperature on both instruments was investigated under two soil salinity levels at two sites.

To accomplish objective two electromagnetic induction mapping at varying soil water content was carried out and the temporal stability analysis was applied to capture the time invariant properties of the soil, such as texture. Geo-referenced EC<sub>a</sub>
measurements were taken using a DUALEM-1S ground conductivity meter on six different days with volumetric water content ($\theta_v$) ranging from 0.11 to 0.23 on a 50 × 50 m agricultural field at Utah State University's Greenville Farm where a gravelly patch was known to exist in the subsurface in an otherwise homogeneous low EC$_a$ Millville silt loam alluvial soil.

To accomplish objective three an EMI imaging approach of the subsurface of the 38 ha Reynolds Mountain East (RME) watershed near Boise, Idaho was presented using kriging to interpolate, and Sequential Gaussian Simulation to estimate the uncertainty in the maps. The idea of difference EC$_a$ mapping was also explored to try and make use of changes in soil moisture to identify more hydrologically active locations. In addition a digital elevation model was used to predict the location of flow paths and to compare these with the EC$_a$ measurement as a function of distance. Finally a more traditional calibration of EC$_a$ with clay percentage was performed across the watershed and soil water holding capacity was determined.

To accomplish objective four EMI mapping was used as a method of densely sampling the subsurface of the RME watershed to produce an exhaustive map of apparent electrical conductivity – a surrogate property that is well correlated with clay percentage. Due to the relative time-invariant characteristics of textural properties, it was possible to correlate clay samples collected over three seasons to EC$_a$ data from one mapping event. Three kriging methods that integrated various levels of information (clay percentage, EC$_a$, and spatial location) were then applied to produce clay percentage prediction maps.
Leave-one-out cross-validation was used to evaluate the value added by incorporating EC$_a$ data in the kriging techniques.

REFERENCES


CHAPTER 2

COMPARING BULK SOIL ELECTRICAL CONDUCTIVITY DETERMINATION USING THE DUALEM-1S AND EM-38DD EMI INSTRUMENTS

ABSTRACT

Earth conductivity instruments based on the principle of electromagnetic induction (EMI) are extensively used for mapping soil salinity and increasingly for mapping soil texture. Environmental variables such as temperature can impact sensor response beyond the effect of soil solution electrical conductivity. This study was conducted to compare the bulk soil electrical conductivity ($EC_a$) – depth relationship between the DUALEM-1S and Geonics EM38-DD devices and to determine the effect of variable temperature environments on instrumental response. The relationship of $EC_a$ to the depth below ground was investigated by raising each instrument in increments of 0.15 m up to 1.8 m above ground. The effect of temperature on both instruments was investigated under two soil salinity levels at two sites. The instruments correspond reasonably with theoretical models describing the $EC_a$ – depth relationships which are primarily coil-orientation dependent. Under the effect of variable temperature test conditions, both instruments were prone to a higher margin of error (10-40%) at lower $EC_a$ readings while the error becomes less significant (~5%) at higher $EC_a$ (>100 mS m$^{-1}$.

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The difference in response of the instruments can be ascribed to the temperature-dependent change in soil EC \( a \) due to a 20°C diurnal temperature variation in addition to instrumental drift caused by temperature effects on the processing circuitry. The EM38-DD’s real-time display and internal powering are its advantages while the lower priced DUALEM-1S does not need instrument calibration and can store data internally.

INTRODUCTION

Electromagnetic induction (EMI) instruments have been used extensively to make non-invasive apparent electrical conductivity (EC \( a \)) measurements, which can be used to characterize soil salinity spatial variability over large areas (Corwin, 2005). EMI instruments are cost-effective and are gaining wider use due to their non-destructive nature, rapid response and ease of integration into a mobile platform, from which real-time measurements can be made. EMI-based EC \( a \) measurements can be used in conjunction with soil sampling, directed from the EC \( a \) surface response (Lesch et al., 1995a, 1995b). The application in field-scale studies is to infer soil spatial variability and to identify field-scale heterogeneities (Corwin and Lesch, 2003). Several factors influence EC \( a \) measurements including soil salinity, water content, porosity, structure, temperature, clay content, mineralogy, cation exchange capacity (CEC), and bulk density (Rhoades et al., 1999; Friedman, 2005). EMI-based EC \( a \) measurements can be used as proxy for inferring the above soil properties by assuming relative homogeneity in all but the property of interest.
EMI-based EC<sub>a</sub> measurements with the Geonics EM38 (Geonics Inc, Mississauga, ON, Canada) have been used by researchers attempting to infer different properties and characterize a wide range of processes at the field-scale for a host of different applications (Hendrickx and Kachanoski, 2002). Doolittle et al. (1994) estimated claypan depth via EC<sub>a</sub> measurements in central Missouri soils via direct calibration between EC<sub>a</sub> and topsoil depth above the claypan. Jaynes et al. (1995) correlated EMI-derived EC<sub>a</sub> measurements to herbicide partition coefficients in order to predict herbicide application leaching potentials in specific areas of the EMI-surveyed field. Anderson-Cook et al. (2002) exploited the positive correlation between EC<sub>a</sub> and previous year crop yields to statistically classify four different soils. Sudduth et al. (2001) developed a procedure employing EC<sub>a</sub> measurements to infer topsoil depth in claypan soils. Corwin and Lesch (2003; 2005) outline standard operating procedure for EC<sub>a</sub> surveys applied to precision agriculture; specifically surveys which calibrate EC<sub>a</sub> to the electrical conductivity of saturation extract samples (EC<sub>e</sub>) for use in salinity studies, and discuss several different applications of field-scale EC<sub>a</sub> maps. Corwin and Lesch (2003) employed EC<sub>a</sub> measurements to infer EC<sub>e</sub> in order to assess salinity effects by comparing EC<sub>e</sub> measurements within fields to crop yields and chemical analyses. Taylor et al. (2003) have used the recently developed DUALEM-2 (DUALEM Inc, Milton, ON, Canada) to identify the locations and depths of septic-system failure.

The reliability of data collected using EMI instruments depends on the thermal stability of the instrument, while the EC<sub>a</sub> measurement averaging over the soil profile depends on the configuration of the instrument coils (Wait 1951; 1955). Researchers
using the EM38 for field mapping have observed progressive instrumental drift affecting the ECₐ measurements during mapping days (Sudduth et al., 2001; Robinson et al., 2004). Sudduth et al. (2001) investigated accuracy issues in the collection of soil ECₐ data and recommended a calibration to document and adjust for instrument drift. EM38 data were collected at four 50m calibration transects during the day, whereby a maximum of over 10% ECₐ deviation was observed. Robinson et al. (2004) on the other hand were able to register a drift of 20% in the “hot” southwest USA where the EM38 instrument panel temperature reached 60°C.

The depth weighted response of an EMI instrument depends on coil orientation with respect to the half space and spacing of the coils (Wait 1951; 1955). Rhoades et al. (1999) have conducted several studies to determine the ECₐ-depth distributions for the measurement of salinity profiles and for analyzing saline seeps. The ECₐ-depth relation is calculated by successively raising the EMI instrument and measuring the respective contribution of each soil interval to ECₐ (Corwin and Rhoades, 1982). Corwin and Rhoades (1990) have produced empirical calibration and statistical analysis equations to calculate the ECₐ-depth relationships for different soil types using the EM-38.

The purpose of this study was to characterize the DUALEM-1S instrument and compare it with the Geonics EM38-DD. Characterization of the ECₐ averaging with depth was conducted on low and high ECₐ soils, and compared with theoretical models. Side-by-side experiments were conducted to compare instrument thermal stability on low and high ECₐ soils.
THEORETICAL CONSIDERATIONS

Ground conductivity meters pass an alternating current through a transmitter coil which produces a primary magnetic field \( H_p \). The primary magnetic field induces small alternating currents in the soil. The induced current loops produce an induced magnetic field \( H_i \) proportional to the current within the loops. The secondary magnetic field, a combination of the primary and the induced magnetic fields \( H_s = H_p + H_i \), induces a small alternating current in a receiver coil. The receiver coil measures the amplitude and phase of the secondary magnetic field, which consists partly of signals from soil layers at differing depths corresponding to the different loops. All of the measured signals are amplified and summed into an output voltage, which is directly related to a depth-weighted average \( EC_a \) calculated from (McNeill, 1980):

\[
EC_a = \frac{4}{2\pi f \mu_o s^2} \left( \frac{H_s}{H_p} \right)
\]

[1]

where \( f \) is frequency [Hz], \( \mu_o \) is the permeability of free space \( (4\pi \times 10^{-7} \text{ H m}^{-1}) \), \( s \) is the inter-dipole spacing [m], \( H_s \) is the secondary magnetic field at the receiver coil [H m\(^{-1}\)] and \( H_p \) is the primary magnetic field at the transmitter coil [H m\(^{-1}\)].

The amplitude and phase of the secondary magnetic field measured by the receiver coil differ from the primary field owing to soil properties, transmitter-receiver spacing and orientation (i.e. horizontally or vertically oriented) with respect to the soil surface (Hendrickx and Kachanoski, 2002).

The transmitters and receivers of EMI devices consist of wound coils which can be treated as magnetic dipoles since the separation between transmitters and receivers is
more than several coil diameters. The magnetic field from each dipole penetrates the earth and the vertical dipole has a greater depth of penetration than the horizontal dipole because the vertical field couples more effectively with material down in the earth than the horizontal field. Figure 2-1 shows that the magnetic fields of the vertical dipoles entering the soil surface are more dense than the horizontal dipoles.

The differing convention used by manufacturers to describe the orientation of the transmitter-receiver system of ground conductivity instruments is confusing to users. The EM38 can be oriented in two different modes; it can either stand in its vertical mode or lay in a horizontal mode. The DUALEM-1S instrument geometry is cylindrical with a directional arrow that indicates one orientation direction, pointing skyward for correct measurement. We will be using the dipole orientation of the transmitter followed by the receiver to identify the different orientations of the two instruments.

In Figure 1, the three combinations are illustrated. I **Horizontal - Horizontal (H-H):** In this combination, both the transmitter and receiver dipoles are oriented parallel to the earth’s surface. The bottom unit (horizontal dipole mode) in the EM38-DD uses this combination. II **Vertical – Vertical (V-V):** In this combination the dipoles are oriented perpendicular to the earth’s surface. The top unit (vertical dipole mode) in the EM38-DD and the horizontal co-planar (HCP) mode in the DUALEM-1S use this combination. III **Vertical - Horizontal (V-H):** The transmitter dipole is vertical, while the receiver dipole is horizontal and its axis intersects the transmitter. The perpendicular (PRP) mode in the DUALEM-1S uses this combination.
Relative Response

The governing equations for the EMI relative response, $\phi$, of the three different orientations are (McNeill, 1980; Wait, 1962):

$$\phi_{V-V}(z) = \frac{4z}{(4z^2 + 1)^{\frac{3}{2}}} \quad [2]$$

$$\phi_{H-H}(z) = 2 - \frac{4z}{(4z^2 + 1)^{\frac{3}{2}}} \quad [3]$$

$$\phi_{V-H}(z) = \frac{2}{(4z^2 + 1)^{\frac{3}{2}}} \quad [4]$$

where $z$ is the depth divided by the transmitter-receiver spacing.

Figure 2-2A shows the relative sensitivity of the three coil-orientations relative to an increase in depth. Both the H-H and V-H orientations are sensitive at the surface, and rapidly lose their sensitivity with an increase in depth. The V-V orientation is insensitive at the ground surface but the sensitivity rapidly increases with depth, peaking at 0.4 m.

Cumulative Response

The EMI cumulative response, $R$, is related to the relative response with the following equation (McNeill, 1980)

$$R(z) = \int_{z}^{\infty} \phi(z) dz \quad [5]$$

Equations for the cumulative response of different orientations from a depth ($z$) to infinity have been given by McNeill (1980) and Wait (1962). We have adopted the
equations so that they give cumulative responses from the surface to a given depth (z) of each orientation (Figure 2-2B).

\[ R_{V-H}(z) = 1 - \frac{1}{(4z^2 + 1)^{1/2}} \]  

[6]

\[ R_{H-H}(z) = 1 - (4z^2 + 1)^{1/2} + 2z \]  

[7]

\[ R_{V-V}(z) = \frac{2z}{(4z^2 + 1)^{1/2}} \]  

[8]

Since the cumulative response is exponential, we need to define a depth beyond which the orientation response is relatively insensitive – the depth of exploration (DOE). For our study we have defined the DOE to be the depth where 70% of the cumulative response comes from. The DOE for the V-V orientation is 1.5 m, while the H-H and V-H orientations achieve the same response at a DOE of 0.75 m and 0.5 m, respectively (Figure 2-2B).

In a layered earth, \( EC_a \) is calculated by summing the conductivity and depth weighted contribution of each layer. In a system with three distinct layers overlying uniform earth, the bulk electrical conductivity is given by (McNeill and Bosnar, 1999):

\[ EC_a = \sigma_1[1 - R(Z_1)] + \sigma_2[R(Z_1) - R(Z_2)] + \sigma_3[R(Z_2) - R(Z_3)] + \sigma_4[R(Z_3)] \]  

[9]

where \( \sigma_{1,2,3} \) are the conductivities of each corresponding layer, \( \sigma_4 \) is the conductivity of the uniform earth underlying the three layers, and \( R(Z_{1,2,3}) \) is the cumulative response at the bottom of each respective layer.
MATERIALS AND METHODS

Instrument Description

The DUALEM-1S (DUAL-geometry Electro-Magnetic) is a geo-conductivity sensor with a transmitter operating at the frequency of 9 kHz and two receivers with different orientations (Table 2-1). In the horizontal co-planar geometry (HCP), hereafter referred to as V-V\textsubscript{DLM}, both the transmitter and the receiver – with a one meter separation – use vertical dipoles. The other setup, perpendicular geometry (PRP), will be referred to as V-H\textsubscript{DLM} hereafter, still uses a vertical dipole transmitter while the receiver located 1.1 meters away uses horizontal dipole. The DOE for the V-V\textsubscript{DLM} setup is about 1.5 m while for the V-H\textsubscript{DLM} it is about 0.5 m. The transmitter and the receiver, as well as the processing circuitry, are housed in a fiber/resin composite casing. The instrument does not come with a display unit and data is transmitted serially through a 9-socket DB-9 connector. The instrument outputs the apparent conductivity and in-phase readings of both orientations; the roll and pitch of the instrument; as well as the time of the data recording, the applied voltage and the internal temperature of the sensor. The instrument is capable of storing 50,000 records in its internal memory for further access.

The EM38-DD is constructed by integrating two standard EM38 ground conductivity meters mechanically and electrically. The bottom instrument’s transmitter-receiver dipoles are oriented parallel to the earth (H-H\textsubscript{EM38} hereafter), while for the top instrument, which controls the digital output of the whole instrument, the dipoles are oriented perpendicular to the earth surface (V-V\textsubscript{EM38} hereafter). In the V-V\textsubscript{EM38} mode the primary magnetic field can effectively penetrate to a depth of 1.5 m, while the H-H\textsubscript{EM38}...
mode is effective for shallower investigation (0.75 m). The EM38-DD comes with two LCD display units on each instrument and also outputs apparent conductivity and in-phase response of secondary to primary magnetic field readings for both orientations. The instrument was calibrated at Greenville Farm for phasing and instrument zeroing using the manufacturer's standard calibration method after a warm up period of 1 hour. Calibration of the EM-38DD requires that the top instrument in the V-V$_{EM38}$ mode reads twice the EC$_a$ value of the instrument in the H-H$_{EM38}$ mode when held 1.5 m above the earth surface.

**Study Sites**

*Greenville Farm (Millville Series):* The Millville series located at the Utah Agricultural Experiment Station (UAES) Greenville Farm has a mean annual precipitation of 422 mm and the mean annual temperature is 8.6°C. The site has a xeric soil moisture regime and a mesic soil temperature regime. The area surrounding the Millville soil pedon is used for irrigated crops and a distinguishable plow layer is observed in the A horizon. The pedon contains less than 1% rock fragments and the texture (silt loam) is uniform with depth. The pH of 8.2 is due to the highly disseminated calcium carbonate. The parent material of the Millville soil is a fine textured alluvium (sилts, very fine sand) due to lower energy distal fan/ overbank flood deposits. The soil is classified as a coarse-silty, carbonatic, mesic Typic Haploxeroll. Soil samples were taken every 0.3m down to a depth of 1.5 m and were analyzed for water content using oven drying, EC$_e$ was measured using the saturation paste extraction method (Soil Survey Staff, 2004) (Figure 2-3A).
*Cache Junction Farm (Cache Series):* The Cache series located at UAES's new farm in Cache Junction has a mean annual temperature of 6.6°C and mean annual precipitation of 445 mm. The site has a xeric and aquic soil moisture regime and a mesic soil temperature regime. The soil is mostly formed from lacustrine deposits derived from limestone and quartzite. The pedon is a polygenetic soil and the parent material for the top soil layer is probably alluvial deposits from the mountains surrounding the site. The soil is classified as a fine silty, mixed, superactive, mesic Typic Natrixeralf. Soil samples were taken every 0.3m down to a depth of 1.5 m and were analyzed for water content and ECₑ as previously described (Figure 2-3D).

**Measurement Response vs Depth**

To study the effect of depth on measurement response, the instruments were lifted from the ground surface to conduct depth sounding. The instruments were raised using a PVC pipe as a guiding support, keeping the instrument parallel to the ground. Five sets of measurements for each instrument were taken at the two study sites by lifting the instruments in increments of 0.15 m up to 1.8 m above the ground. The measurements were obtained directly from the EM38-DD display, while an Allegro CX with HGIS software was used to collect the measurements from the DUALEM-1S.

**Measurement Response vs Temperature**

In order to study the effects of temperature, EM readings from the two instruments were recorded throughout the day at two locations with high and low ECₑ values. On July 1, 2005, the instruments were placed at the Greenville farm and on July 8
the instruments were positioned at the Cache Junction Farm. At both locations, the instruments were separated by a distance of 4 meters and the measuring instruments were placed midway between them. A CR10 data-logger (Campbell Scientific, Logan, UT) was used to record the readings from the six thermocouples placed on the instruments (a thermocouple each by the receiver dipoles and panel of the EMI instruments) and the surrounding environment (one 0.15 m below ground and another 0.3 m above ground in the air). The EM38-DD data was acquired using Handheld-GIS (HGIS, StarPal Inc., Fort Collins, CO) program inside an Allegro CX hand-held field computer (Juniper Systems, Logan, UT). The DUALEM-1S data was recorded internally and later downloaded to a computer.

RESULTS AND DISCUSSION

Measurement Response vs Depth

Data from Cache Junction and Greenville Farm was used to determine the EC$_a$-depth relationship of the different orientations of the two instruments. This data can be used in conjunction with EC$_a$ layer models, such as Eq. (9) to invert the data to determine the approximate bulk conductivity of the soil layers. Performing the inversion is a way of comparing the data collected with the two instruments. When the instruments are raised above the earth’s surface, the cumulative response for each step is reduced correspondingly by the effect of the height above the ground. The EC$_c$ and water content measurements with 0.3 m depth increments are presented in Figure 2-3A and 2-3D for the two soils. These data show that the Greenville Farm data had a higher EC$_c$ layer over
two lower EC\textsubscript{e} layers (Figure 2-3A) and that the Cache Junction site had a higher conductivity layer between two lower conductivity layers (Figure 2-3D). We tried two inversion approaches, the first assuming a uniform earth using Eqs (6) – (8); and the second assuming three layers over a uniform earth (Eq. (9)) based on the observed changes in EC\textsubscript{e} as a function of depth (Figure 2-3A and D). We chose layer depths for the Greenville Farm and Cache Junction sites of 0 – 0.6, 0.6 – 1.2, 1.2 – 1.5 m, corresponding approximately with the observed changes in EC\textsubscript{e} with depth. The predicted EC\textsubscript{a} response was then fitted to the measured EC\textsubscript{a} response by minimizing the error between the two and by allowing the bulk conductivity of the three layers and the uniform earth to vary.

The results for the Greenville farm are presented in Figure 2-3B and C. The broken lines show the fit for the uniform earth and demonstrate a poor fit with the data for both instruments. The application of the three-layer inversion improves the fit for the DUALEM-1S data but is still poor for the EM38 data. The root mean square error (RMSE) for the DUALEM-1S over a uniform earth was 0.30 for V-V\textsubscript{DLM} and 0.27 for the V-H\textsubscript{DLM}, respectively. This improved to RMSE of 0.09 and 0.05 for V-V\textsubscript{DLM} and V-H\textsubscript{DLM} for the three-layer model. The result of the inversion is presented as the dotted line in figure 3A, and, although providing a good fit, it fails to capture the dominant higher conductivity layer over the two lower conductivity layers.

The EM38-DD showed the largest divergence from the models; V-V\textsubscript{EM38} having a RMSE of 0.79 and H-H\textsubscript{EM38} having a RMSE of 1.2 for the uniform earth model. Interestingly the use of the three-layer model did not lead to a major improvement with
RMSE of 0.54 and 1.00 for V-V_{EM38} and H-H_{EM38}, respectively. The difference between the measured and modeled data for the EM38-DD is due to the difficulty calibrating the EM38-DD at low conductivity values, resulting in poor quality measurements. In order to achieve a calibration with V-V_{EM38} reading twice H-H_{EM38}, the EC of the horizontal had to be raised, this sets a threshold below which EC cannot be measured resulting in poor data at low conductivities for this soil.

The measurements made in the Cache Junction soil are presented in Figure 2-3E and F. In this higher conductivity soil, the uniform earth model correlated well with the data from both instruments. The fitting to the DUALEM-1S data gave a RMSE of 1.7 V-V_{DLM} and 2.2 V-H_{DLM} (Figure 2-3E). The EM38-DD was better giving a RMSE of 0.88 for the V-V_{EM38} orientation and 1.4 for H-H_{EM38} orientation (Figure 2-3F). The use of the three-layer model improved the RMSE for the DUALEM-1S to 0.19 V-V_{DLM} and 0.16 V-H_{DLM} and marginally for the EM38-DD to 0.80 V-V_{EM38} and 1.4 H-H_{EM38}. The results of the inversion at Cache Junction for the DUALEM-1S are presented in figure 3D. This time the inversion does a better job of picking out the high and low conductivity layers. The use of these models demonstrates the different abilities of the instruments to measure under different conditions bringing out the important point that with a small range of EC_a response (0-20 mS m^{-1}), the DUALEM-1S does much better than the EM38-DD due to its internal, automatic calibration. The application of these simple inversion models shows that the results leave much to be desired. Inversion of this data could be very useful in vadose zone research for determining depth to conductive layers (salts, water tables or clay layers), and should form the basis of future research with these instruments.
**Measurement Response vs Temperature**

Both instruments were placed on bare soil while EC and temperature data were collected from 10:30 AM to 6:30 PM. At the low conductivity site (Greenville), the air temperature ranged from 24°C to 40°C while the soil temperature climbed from 18°C to 32°C at 0.15 m below the soil surface. The instrumental temperature variations of the DUALEM-1S and the EM38-DD are presented in Figure 2-4A and 2-4B, respectively. The DUALEM-1S casing reached a maximum temperature of around 40°C while the maximum temperature for V-V panel was above 50°C. Figure 4C and 4D show the EMI responses of the coil orientations of the DUALEM-1S and EM38-DD respectively. The mean response of the V-V was 8.05 mS m⁻¹ with a standard deviation (SD) of 0.87 and the V-H had a mean response of 10.4 mS m⁻¹ with a SD of 0.35, whereas the mean response of the V-V was 19.9 mS m⁻¹ with a SD of 1.7 and the H-H had a mean response of 19.6 mS m⁻¹ with a SD of 1.4.

Meanwhile at the high conductivity site (Cache Junction), the air and soil temperature were close to each other ranging from 20°C to 35°C. The instrumental temperature variations of the DUALEM-1S and the EM38-DD are presented in Figure 2-4E and 2-4F, respectively. The EMI responses of the four coil orientations of the two instruments are shown in Figure 2-4G and 2-4H. For the EM38-DD, the mean response of the V-V was 109 mS m⁻¹ with a SD of 1.2 and the H-H had a mean response of 72.2 mS m⁻¹ with a SD of 1.1. In the case of the DUALEM-1S, the mean response of the V-V was 108 mS m⁻¹ with a SD of 1.4 and the V-H had a mean response of 50.4 mS m⁻¹ with a SD of 0.18. The difficulty of calibrating the EM38-DD in low EC
soils is not a problem at Cache Junction (high conductivity site) and, as theoretically expected, \( V-V_{\text{DLM}} \) and \( V-V_{\text{EM38}} \) show similar EMI response.

It is evident from the statistics that a larger EMI response deviation from the initial reading is observed when the instruments are measuring low \( \text{EC}_a \) values. At the low conductivity site, the EM38-DD had a maximum difference of 23% (6.3 mS m\(^{-1}\)) for the \( V-V_{\text{EM38}} \) and 22% (8.3 mS m\(^{-1}\)) for \( H-H_{\text{EM38}} \). The maximum difference for the DUALEM was 13% (1.8 mS m\(^{-1}\)) for \( V-H_{\text{DLM}} \) and a high 42% (4.8 mS m\(^{-1}\)) for \( V-V_{\text{DLM}} \). The percentage difference in the EMI readings during the day at the high conductivity site was much smaller than at the low conductivity site. Maximum differences of 5.2% (6.4 mS m\(^{-1}\)) and 6.6% (8.0 mS m\(^{-1}\)) were observed for \( V-V_{\text{EM38}} \) and \( H-H_{\text{EM38}} \), respectively, while maximum differences of 5.0% (5.7 mS m\(^{-1}\)) and a low 1.2% (1.1 mS m\(^{-1}\)) were recorded for \( V-V_{\text{DLM}} \) and \( V-H_{\text{DLM}} \), respectively.

The difference in response can be ascribed to two things: 1) the change of temperature of the soil during the day that would tend to increase the ground conductivity, and 2) instrument drift caused by the inability of the processing circuitry to fully compensate for instrument heating. In order to differentiate between these two competing factors we model \( \text{EC}_a \) to determine what the response of the instruments should be in the soil. As inputs for the model we use water content measured from soil samples, porosity, and soil temperature measured at 0.15 m depth. We recognize that by using the temperature measured at 0.15 m the values will be an upper bound to the actual \( \text{EC}_a \) sensed by the instruments. However, we would expect both instruments to show a trend similar to the modeled \( \text{EC}_a \).
An extended version of Archie’s Law (Friedman, 2005), accounting for unsaturated conditions was used to model the expected ground conductivity response that the EMI instruments would measure. We adopted Friedman’s (2005) simplification which uses a unit value as the exponent of porosity (n), thus obtaining an equation with only one empirical fitting parameter (d):

\[ EC_a = EC_e \frac{\theta_v^d}{n} \]  

where \( \theta_v \) is volumetric water content, \( n \) is porosity and \( d \) is an empirical fitting parameter, and according to Corwin and Lesch (2005):

\[ EC_e = EC_e(\text{initial}) + EC_e(\text{initial}) \times (\Delta Temp \times 0.02) \]  

The modeling was conducted such that each orientation will measure 70% of the cumulative response. The V-V\textsubscript{EM38} and V-V\textsubscript{DLM} achieve this by measuring down to a depth of 1.5 m while the V-H\textsubscript{DLM} and H-H\textsubscript{EM38} attain such a response by measuring down to 0.5 m and 0.75 m respectively. The parameter \( d \) was chosen in order to fit the first point of the model to the first data point at the beginning of the experiment. The model derived experimentally using coarse textured soils has its limitations in clay soils, but demonstrates the expected upward trend in \( EC_a \) as temperature increases. Table 2-2 lists the parameters used for modeling the responses of the different coil orientations at the two sites.

The model prediction and the EMI response compare best at the low conductivity site at Greenville Farm (Figure 2-4C and 2-4D). The EMI responses for both the EM38-
DD coil orientations in Figure 2-4D seem to follow the model for the first 100 minutes and then abruptly start to decline against the prediction of the model. The EMI responses deviate from the model when the panel temperature exceeds 45 °C, and the slope of the decline flattens once the panel temperature is below 45 °C, similar to the findings of Robinson et al. (2004). In the case of the DUALEM-1S (Figure 2-4C), the V-V\textsubscript{DL}M starts deviating from the model after few minutes and the decline slope flattens once the casing temperature starts dipping towards 40 °C at about 300 minutes after the start of the experiment. The EMI response of the V-H\textsubscript{DL}M closely follows the expected response predicted by the model and appears not be affected by instrument drift unlike the other orientations. In Figures 2-4G and 2-4H at Cache Junction (high conductivity), the model suggests an expected increase in EC\textsubscript{a} as the temperature increases. However, both the DUALEM-1S and EM38-DD EC\textsubscript{a} measurements decline. This is most likely due to drift caused by high temperatures. The data indicate that, 30 minutes after the start of the experiment, casing and panel temperatures were 40 °C and increased further. The decreased EC\textsubscript{a} response of the instruments is again consistent with the findings presented in Robinson et al. (2004).

**General Observations**

Some of the strong features of the EM38-DD are: a real-time LCD display, a built-in handle, portable internal powering and years of applied research experience; while a complicated instrumental calibration procedure, exposed control knobs and a commonly over-heating black panel are drawbacks. The DUALEM-1S has avoided some of the problems associated with the EM38-DD by not having any control knobs, having a
yellow casing to minimize radiation absorption and by incorporating an automatic instrument calibration. This automated instrument calibration is a distinct advantage for users working with low conductivity soils, for instance, when used for texture mapping.

Even though the DUALEM-1S can store 50,000 records in its internal memory, it lacks a built-in display unit making an external logging or display unit necessary. The DUALEM-1S also requires an external power source and does not come with a handle for manual measurements. This means the instrument is less suited to one-off measurements and more suited to applications such as mobile mapping where continuous measurements are made. At the time of testing, the price of the DUALEM-1S was approximately two-thirds the cost of the EM38-DD. Both instruments can be connected to various logging programs running on hand-held field computers or laptops for recording geo-referenced EMI response while field mapping.

**CONCLUSIONS**

$EC_a$ response measurement down a profile can be useful in determining depth to conductive layers (salts, water tables or clay layers), aiding researchers involved in agriculture and hydrology; but one needs to be aware of the limitations of the EMI instrument used. The measured response of the instruments with depth could be better fitted to inverse models using the DUALEM-1S data as compared to the EM38-DD output. This was much more apparent for measurements in the low conductivity soil where instrument calibration difficulty made data inversion unfeasible using the EM38-DD. Results from the simple three-layer model over a conductive earth indicate that
advanced optimization techniques or inversion models are required to obtain improved predictions of conducting layer structure.

Our measurements over a range of temperatures indicate that at low $EC_a$ both the EM38-DD and DUALEM-1S are more susceptible to instrument drift; this reduces considerably at higher values of $EC_a$. The $V$-$H_{DLM}$ configuration of the DUALEM-1S appears to correspond well with predicted values of $EC_a$ at low bulk soil EC values. The EM38-DD readings appeared to be more temperature sensitive at lower $EC_a$ exhibiting the opposite trend to the expected increase in $EC_a$ as temperature increased. An improved method of temperature correcting for the instruments is required and should improve the accuracy of the instruments. For those using these instruments for an extended period to map soil properties (e.g. soil texture) where $EC_a$ values tend to be low, we recommend that the mapping is performed on a cooler day or that the instruments are protected from direct sunlight. In this instrument comparison the EM38-DD’s real-time display and internal powering proved to be its advantages while the lower priced DUALEM-1S is less temperature sensitive, does not require manual instrument calibration and can store data internally.

REFERENCES


Table 2-1. Technical Specifications of the EM38-DD and DUALEM-1S

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<th>EM38-DD</th>
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<tr>
<td>Operating frequency</td>
<td>14.6 kHz / 17 kHz</td>
<td>9 kHz</td>
</tr>
<tr>
<td>Power Supply</td>
<td>2 internal 9 Volt batteries</td>
<td>External 12 V DC</td>
</tr>
<tr>
<td>Instrument dimensions</td>
<td>1.06 x 0.15 x 0.18 m</td>
<td>1.41 m long, 0.09 m diameter</td>
</tr>
<tr>
<td>Instrument weight</td>
<td>6.8 kg</td>
<td>5 kg</td>
</tr>
<tr>
<td>Conductivity Range</td>
<td>1000 mS m(^{-1})</td>
<td>3000 mS m(^{-1})</td>
</tr>
</tbody>
</table>
Table 2-2 Soil parameters for modeling the effect of soil temperature on apparent electrical conductivity (ECₐ) using Eq. (10).

<table>
<thead>
<tr>
<th></th>
<th>Greenville Farm</th>
<th>Cache Junction</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>θₜ, ECₑ, n, d</td>
<td>θₜ, ECₑ, n, d</td>
</tr>
<tr>
<td>V-VₑM₃8</td>
<td>0.250 0.538 0.450 1.25</td>
<td>0.359 3.00 0.550 1.54</td>
</tr>
<tr>
<td>V-VₑD₃M</td>
<td>0.250 0.538 0.450 1.73</td>
<td>0.359 3.00 0.550 1.55</td>
</tr>
<tr>
<td>V-HₑD₃M</td>
<td>0.254 0.695 0.450 2.00</td>
<td>0.371 2.38 0.550 2.17</td>
</tr>
<tr>
<td>H-HₑM₃8</td>
<td>0.251 0.609 0.450 1.44</td>
<td>0.375 2.88 0.550 2.02</td>
</tr>
</tbody>
</table>
Fig. 2-1. Transmitter and receiver dipole orientations of the EM38-DD and DUALEM-1S (Instruments are oriented parallel to the surface). The loops of wire form a solenoid and a dipole is created when current passes through the wire. The EM38-DD, instrument on top, has its transmitter and receiver dipoles oriented in Horizontal – Horizontal (H–H) and Vertical – Vertical (V–V) modes. The DUALEM-1S, on bottom, also utilizes a V–V and a Vertical - Horizontal (V–H) mode for the dipoles in its transmitter and receiver.
Fig. 2-2. Relative sensitivity (A) and cumulative (B) response with respect to depth of the three coil orientations of the DUALEM-1S and EM38-DD.
Fig. 2-3. Profile $\text{EC}_e$, $\theta_v$, and $\text{EC}_a$ (inversion) data (A,D) and $\text{EC}_a$ – height above ground relationships as modeled using uniform earth and three-layer models for the DUALEM-1S (B,E) and EM38-DD (C,F) at Greenville Farm and Cache Junction sites.
Fig. 2-4. The EMI response of the EM38-DD and DUALEM-1S at Greenville Farm and Cache Junction throughout the day. (A,B) and (E,F) show the variation of the temperature for both instruments as well as air and soil temperature at Greenville Farm and Cache Junction respectively. (C,D) and (G,H) present the EMI response of both instruments as well as the predicted EMI response using Archie’s extended model (Eq. 10) for Greenville Farm and Cache Junction respectively.
CHAPTER 3

ELECTROMAGNETIC INDUCTION MAPPING AT VARIED SOIL MOISTURE REVEALS FIELD-SCALE SOIL TEXTURAL PATTERNS

ABSTRACT

Knowledge of the spatial distribution of soil textural properties is important for determining soil moisture storage and soil hydraulic transport properties. But there is difficulty in capturing the heterogeneity without exhaustive sampling and costly sample analysis. Our objective was to investigate the use of electromagnetic induction (EMI) mapping at challengingly low apparent electrical conductivity (ECa) soils at varying soil water content in order to capture the time invariant properties of the soil, such as soil texture. Geo-referenced ECa measurements were taken using a DUALEM-1S ground conductivity meter on six different days with volumetric water content (θv) ranging from 0.11 to 0.23 on a 50 × 50 m agricultural field where a gravelly patch was known to exist in the subsurface in an otherwise homogeneous Millville silt loam alluvial soil. Ordinary block kriging was used to predict ECa at unsampled areas to produce 1-m resolution maps. Temporal stability analysis was used to divide the field into three regions exhibiting distinct ECa patterns. Subsequent ground-truthing confirmed that the lowest conductivity region is associated with a high energy channel that deposited coarser

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2 The material for this chapter is currently in review as: Abdu, H., Robinson, D.A., Boettinger, J. and Jones, S.B., Electromagnetic Induction Mapping at Varied Soil Moisture Reveals Field-Scale Soil Textural Patterns, Soil Sci. Soc. Amer. J.
materials in the formation of the soil. There was also a statistically significant difference (p=0.023) in the average fine particle percentage between the other two delineated regions. Mapping at $\theta_v$, just below field capacity reveals greater textural variability and is recommended where resources allow only one mapping event. These maps could be informative for modeling, experimental design, sensor placement and targeted zone management strategies in soil science, ecology and hydrology, as well as in agricultural applications.

**INTRODUCTION**

The quantitative determination of the spatial properties of soils at the field scale remains a research challenge. The development of precision agriculture with the targeted application of fertilizer or irrigation could be further enhanced with improved, quantitative, soil textural data at the field scale. Geophysical methods are gaining more acceptance as a way of obtaining spatially distributed data that can be correlated with soil spatial properties (Corwin, 2005). Given techniques such as ground penetrating radar or electromagnetic induction (EMI), the subject of this paper, we need to determine efficient ways to extract useful information. Mapping protocols and calibration procedures have been developed for soil salinity surveys. However, in non-saline agricultural soils we are often interested in the spatial delineation of soils with different characteristics, usually textural differences, with the minimum amount of soil sampling and laboratory calibration which adds expense to surveying.
In this paper we develop and test a new procedure for mapping non-saline soils to differentiate static soil characteristics from dynamic ones. We consider soil texture as a dominant static property, whereas soil water content is a dynamic property that changes rapidly in time. In order to separate these properties we develop a multi-mapping methodology and analysis procedure. This allows us to identify locations offering consistent behavior over a range of soil water content. Given the composite maps produced, decisions can be made as to whether calibration is required, or if the obtained information is sufficient for the purposes of identifying management zones.

Identifying time-invariant static properties such as texture is important as they have a direct influence on the quantity and distribution of dynamic soil properties such as soil water content. Soil water status is critical to plant growth, crop quality, chemical fate and transport, and microbial processes (Hillel, 1998). Soil structure and texture are important properties controlling the hydraulic conductivity and infiltration capacity of a soil system (Davie, 2003). These two properties in turn determine how much water is stored in a soil system as well as how much water is diverted from the system due to runoff. Soil water content is an important factor for many agricultural practices such as the timing of tillage or fertilizer application. More importantly in dry climates, knowledge of the soil water content can reduce water waste and increase efficient use of this precious resource by targeting irrigation more effectively (Hillel, 1998). Thus, knowledge of soil textural properties in space can help to infer soil hydrological behavior.

Traditional soil mapping strategies tend to be subjective and rely on the expertise of the soil surveyor (USDA-NRCS, 1999). Discrete point locations in the form of a pedon
are chosen to sample soil physical and chemical properties in order to determine soil properties for a given soil mapping unit. Thus soil regions are dependent on the original scheme of sampling which in turn is dependent on vegetation coverage, topography, and geological features. While this might be sufficient to classify large areas, it is biased towards grouping and overlooks small scale soil variability, which is important for management and understanding hydrological and ecological patterns. Our understanding of the distribution of subsurface physical properties is also limited by the sparse sampling plan and consequent interpolation method. Thus defining subsurface physical property boundaries remains largely subjective using traditional sampling and survey methods.

Geophysical methods are frequently used in characterizing the subsurface by measuring a surrogate property that is related to underlying physical properties. Some of the popular geophysical methods used for characterizing the subsurface are: Ground-Penetrating Radar (GPR), Electrical Resistivity Tomography / Imaging (ERT/I) and Electro-magnetic induction (Telford et al., 1990; Reynolds, 1997; Rhoades et al., 1999; Rubin and Hubbard, 2006). A GPR system transmits a high frequency (MHz-GHz) electromagnetic (EM) radiation into the subsurface and receives a reflected signal that has been transformed by the electrical properties of the subsurface material. The reflected wave is dependent upon the dielectric permittivity of the various subsurface layers. The application of GPR for spatial soil mapping is restricted by the attenuation of the transmission signal in clayey and highly conductive soils (Weihermuller et al., 2007). An ERT/I system measures the distribution of electrical resistivity in the subsurface by sending a direct current signal into the ground through one set of electrodes and
measuring the induced voltage through another set of electrodes. While the ERT/I technique is a powerful technique for investigating different depths of a transect it tends to be time consuming and most suited to static deployment. An EMI system transmits a low frequency signal (KHz) into the subsurface without the need to establish contact with the ground. The alternating current produces a magnetic field in the subsurface which in turn induces secondary current loops related to the subsurface electrical conductivity. These in turn create secondary magnetic field loops and the instrument measures the superposition of the combined primary and secondary fields (McNeill, 1980; Chapter 2). This non-invasive technique is appropriate for field scale measurement due to its rapid response, ease of integration into mobile vehicular measuring platforms and nondestructive / non-contact requirements.

Apparent electrical conductivity ($EC_a$) is a proxy for subsurface physical properties and provides a measure of charge mobility due to an application of an electric field, and is defined as the ratio between current density ($J$, A m$^{-2}$) and electrical field ($E$, V m$^{-1}$) according to Ohm’s law (Paul, 2004). Several physical and chemical soil properties influence field scale $EC_a$ measurements. Friedman (2005) conveniently partitions the major factors into three categories: bulk soil, solid particle and soil solution. The bulk soil category comprises the factors that are defined by the organization of a three phase soil system such as porosity ($n$) and water content ($\theta$); factors in the solid particle category include particle shape and orientation, particle-size distribution, cation exchange capacity (CEC), and wettability; ionic strength ($\sigma_w$), cation composition and temperature are factors that are classified under the soil solution category.
EMI-based EC<sub>a</sub> measurements have been used by researchers attempting to infer different properties and characterize a wide range of processes at the field-scale for a host of different applications (Hendrickx and Kachanoski, 2002). Some of the applications include: estimating claypan depth (Doolittle et al., 1994); predicting herbicide application leaching potentials in specific areas (Jaynes et al., 1995); petrocalcic horizon depth (Boettinger et al., 1997), inferring topsoil depth in claypan soils (Sudduth et al., 2001); and identifying the locations and depths of septic-system failure (Taylor et al., 2003). Corwin and Lesch (2003; 2005) outline standard operating procedure for EC<sub>a</sub> surveys applied to precision agriculture; specifically surveys which calibrate EC<sub>a</sub> to the electrical conductivity of saturation extract samples (EC<sub>e</sub>) for use in salinity studies, and discuss several different applications of field-scale EC<sub>a</sub> maps.

There are some studies that have used EMI mapping techniques coupled with soil sampling to delineate subsurface properties (Anderson-Coo et al., 2002). Greve and Greve (2004) have applied EMI mapping to better define soil map unit delineation widths. In classical soil mapping, map unit transition zones are represented by lines since it is time consuming and labor intensive to exactly quantify the width of the transition zone (Greve and Greve, 2004). Their study used auger sampling and applied a spatial rate of change calculation on a kriged EMI map to better define the transition zones of the map units. EMI mapping was used to infer the subsurface morphology of an agricultural field to identify areas with offsite agrochemical migration (Wilson et al., 2003). The authors mapped the field for two consecutive days to see the effect of moisture change on EC<sub>a</sub>. They were able to infer that the EC<sub>a</sub> pattern similarity observed after field capacity
was due to soil morphology. Areas with a faster change in conductivity as the field dries were associated with high unsaturated hydraulic conductivity and as prime candidates for chemical migration. Kitchen et al. (2003) investigated the effectiveness of using EMI mapping for delineating productivity zones for agricultural management in claypan soils of Missouri. The study showed that the productivity zones delineated using EC_a and elevation data agreed up to 70% with those delineated from 10 years of combine monitored yield maps. Farahani and Buchleiter (2004) conducted multi-year EC_a surveys to classify sandy and non-saline fields into low, medium and high EC_a zones. They measured the temporal variability of one mapping event from another by investigating how the measurements deviated from the 1:1 line.

Different field experiments have shown that the major properties that contribute to the apparent electrical conductivity of a soil include the electrical conductivity of the soil solution (EC_c), water content and texture (Lesch et al., 1995a,b). Our experiment was designed to test EMI performance at the low end of EC_a measurements. Differences in EC_a between sand and 2:1 clay mineral soils often can range as much as 60 to 100 mS m$^{-1}$. However, in many agricultural soils, textural differences may be more subtle, but still of scientific or economic importance. We chose a 50 × 50 m field site with a relatively uniform silt-loam soil, but on an alluvial fan with relict, subsurface gravel channels that cannot be readily observed from the surface; our objective was to determine if the EMI was sensitive enough to identify the location of these channels. Changes in soil water content could potentially mask differences in soil texture and complicate the interpretation of and electrical mapping of the subsurface in terms of defining boundaries.
Our strategy was to map the field using EMI at a range of soil water contents to try and identify locations with consistently higher or lower EC<sub>a</sub> than the global mean. In addition, analysis was conducted to determine the optimal water content for identifying textural differences. Therefore, the objective of this study was to use repeated EMI mapping and temporal stability analysis at different soil water contents to delineate soil textural patterns in a low EC<sub>a</sub> agricultural field.

**THEORETICAL CONSIDERATIONS**

**Temporal stability analysis**

Vachaud et al. (1985) characterize the time invariant association between spatial location and classical statistical parametric values as the concept of temporal or rank stability. The method depends on a spatial location keeping its rank in the cumulative probability function for different sampling times (Vachaud et al., 1985). In the case of soil water content this has been shown to work relatively well for level ground, but less so for sloping ground (Kachanoski and de Jong, 1988; Grayson and Western, 1998). Since our study area is nearly level and the main assumption is that EMI mapping can capture a time-invariant subsurface physical property through repeated mapping, a temporal stability analysis technique is a good way of quantifying and analyzing the data. We have modified the Vachaud et al. equations as used for moisture storage to apparent electrical conductivity (EC<sub>a</sub>).

For each support block in the field (i) on a mapping event (j), the apparent electrical conductivity is defined as EC<sub>a</sub><sub>ij</sub>. The difference \( \Delta_{ij} \), (Equation [1]), is
evaluated by subtracting the average \( E_{Ca_j} \) for all \( n \) locations, \( \overline{E_{Ca_j}} \), (Equation [2]), from \( E_{Ca_{ij}} \).

\[
\Delta_{ij} = E_{Ca_{ij}} - \overline{E_{Ca_j}} \tag{1}
\]

where

\[
\overline{E_{Ca_j}} = \frac{1}{n} \sum_{j=1}^{n} E_{Ca_{ij}} \tag{2}
\]

The array \( \Delta_{ij} \) is normalized by dividing it by \( \overline{E_{Ca_j}} \) to produce a new variable - the relative difference \( (\delta_{ij}) \).

\[
\delta_{ij} = \frac{\Delta_{ij}}{\overline{E_{Ca_j}}} \tag{3}
\]

For each mapping event, equation [3] is then used to evaluate a column of relative differences for all locations.

Once the relative differences are determined, we then calculate the average relative difference \( (\overline{\delta_j}) \) for each location across \( m \) mapping events, given by:

\[
\overline{\delta_j} = \frac{1}{m} \sum_{j=1}^{m} \delta_{ij} \tag{4}
\]

The standard deviation of the relative differences of a location can also be evaluated similarly. A quantitative measure for testing the time stability between two mapping days is the Spearman’s rank correlation coefficient \( (r_s) \) (Kottegoda and Rosso, 1997), given by:

\[
r_s(j, j') = 1 - \frac{6 \sum_{i=1}^{n} (R_{ij} - R_{ij'})^2}{n(n^2 - 1)} \tag{5}
\]
The test, specified in equation [5], is evaluated by comparing the rank of a support block, \( i \), on a specific mapping event \( j \) (\( R_{ij} \)) to its rank on another mapping event \( j' \) (\( R_{ij'} \)). A rank correlation matrix can be constructed for all the mapping days by evaluating equation [5] for \( j, j' = 1 \) to \( m \), where \( j \neq j' \). The matrix, \( r_s(j, j') \), is an upper triangular matrix with ones in the diagonal. The closer the values of \( r_s(j, j') \) are to 1, the stronger the temporal stability of all the locations in the field.

**Data Transformation Using the Normal Score Procedure**

The underlying assumption of kriging is that the data are normally distributed (Webster and Oliver, 2001). The normal score transform is useful in normalizing many environmental variables that have large outlying values (positively skewed) to provide a normal distribution. The normal score transform function is derived by matching the original skewed cumulative distribution function (cdf) to a standard normal cdf (e.g., Figure 3-1).

Functions \( F(z) \) and \( G(y) \) are cdfs of the original random function (RF) \( Z(x) \) and the standard normal RF \( Y(x) \) respectively (Deutsch and Journel, 1998):

\[
F(z) = \text{Prob}\{Z(x) \leq z\}, \quad G(y) = \text{Prob}\{Y(x) \leq y\}
\]

The transform, \( \phi(\cdot) \), that takes any cdf \( F(z) \) to a standard Gaussian cdf \( G(y) \) is given as

\[
Y(x) = \phi(Z(x)) = G^{-1}[F(Z(x))]
\]

where \( G^{-1}(\cdot) \) is the inverse Gaussian cdf or quantile function of the RF \( Y(x) \).

In algorithm form, the normal score transform procedure can be reduced to the following three steps (Goovaerts, 1997):
1) The \( n \) original data values, \( z(\mathbf{x}) \), are first ranked in ascending order and tied \( z \) values are separated according to the local averages of the data surrounding each tied value.

2) The sample cumulative frequency of the datum \( z(\mathbf{x}) \) with rank \( k \) is then computed as

\[
p_k^* = \frac{k}{n} - 0.5/n
\]

where all data receive the same weight \( 1/n \)

3) The normal score transform of the \( z \) datum with rank \( k \) is matched to the \( p_k^* \)-quantile of the standard normal cdf:

\[
y(\mathbf{x}) = G^{-1}[F^*(z(\mathbf{x}))] = G^{-1}(p_k^*)
\]

**Spatial Prediction**

Kriging relies on an underlying spatial structure of a measured variable in order to predict its value at unsampled locations (Goovaerts, 1999; Webster and Oliver, 2001). Most prediction methods, including kriging, average the weighted values of the adjacent sampled values \( (z(\mathbf{x}_i)) \) in order to predict the variable at the unsampled point \( z^*(\mathbf{x}_0) \).

\[
z^*(\mathbf{x}_0) = \sum_{i=1}^{n} \lambda_i z(\mathbf{x}_i)
\]
The kriging problem simplifies to solving for a vector of weights, $\lambda$, that will minimize a generalized least-squares (GLS) equation. The spatial dependence of the process, represented in the residuals of the GLS regression equation, is solved when:

$$\lambda = C^{-1}c(x)$$  \[11\]

where $C$ is the matrix of covariances, $C(x_i,x_j)$, between all possible pairs of the $n$ sample sites and $c(x_i)$ is a column vector of covariances between the prediction point and each of the $n$ sample sites.

In order to solve for $\lambda$, we need to evaluate the matrix of covariances $C$, which can be done using a semivariogram function, written:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [z(x_i) - z(x_i + h)]^2$$  \[12\]

where the function computes the average squared differences of the values of the random variable $z()$ at a vector of data pairs $x$ and $x+h$, where $N(h)$ is a number of data pairs within a given class of distance. A parametric model is used to describe the experimental semivariogram to provide a continuous, positive and smooth description of the covariance matrix, $C$.

Block kriging extends the above method from a point estimation of a spatially continuous variable to the average value over a small area or block (Deutsch and Journel, 1998). This is useful when the support block of a physical measurement is beyond a point as in EMI measurements.
MATERIALS AND METHODS

Study Site

The field study was conducted in the summer and fall of 2006 and 2007 at the Utah Agricultural Experiment Station’s Greenville Farm located in Cache Valley, Utah, at the geographic coordinates 41°46’1” N and 111°48’40” W. Mean annual precipitation is 422 mm and the mean annual temperature is 8.6°C, providing the site with a xeric soil moisture regime and a mesic soil temperature regime. The area of study was a 50 × 50 m square area with smooth, nearly level topography located on the eastern end of a larger field. The field had been fallow for 2 years at the time of study.

The soil at the Greenville Farm is of the Millville Series. The soil parent material is medium-textured alluvium (silts and very fine sand) deposited as distal fan and overbank flood deposits on the Green Canyon alluvial fan (Figure 3-2A). The soil pH was 8.2 due to the high concentration of disseminated CaCO$_3$. The soil is classified in the family of coarse-silty, carbonatic, mesic Typic Haploxerolls. The typical pedon that represents the soil in most of the study area contains <1% rock fragments and the texture (silt loam) is uniform with depth. However, gravel lenses exist in these fields and become most apparent during soil ripping (J. Slade, personal communication, 2006). Discussion with the farm manager and our visual observations were used to identify the general location of the gravel lens (Figure 3-2B) in what is otherwise a relatively homogeneous soil in the study field. Representative pedons of the gravel-free soil and the soil with the gravel lens were described in backhoe-excavated pits using standard methods.
Instrumentation

A set of eleven 0.15 m TDR probes with thermocouples were setup in a plot near the mapping location in soil representing the gravel-free Millville series in order to measure water content and temperature. The probes were buried from 0.05 m to 2.0 m below the surface and were positioned close to each other at the surface and with greater separation with increasing depth. Volumetric water content, bulk electrical conductivity, and temperature data were collected every 30 minutes. The volumetric water content ($\theta_v$) at 0.5 m was taken to be the water content of the control plot, corresponding to the depth of maximum weighting for the EMI measurement. Hourly rainfall and evapotranspiration data were also collected from a weather station located on an adjacent grass field.

Geo-referenced $E_{Ca}$ measurements were taken non-invasively using the DUALEM-1S ground conductivity instrument along with a Trimble ProXT GPS unit. The DUALEM-1S (DUAL-geometry Electro-Magnetic) is a geo-conductivity sensor with a transmitter operating at the frequency of 9 kHz and two receivers with different orientations. We used the horizontal co-planar geometry (HCP) or V-V$_{DLM}$ mode where both the transmitter and the receiver, with a 1-m separation, use vertical dipoles. The depth of exploration (DOE) for the V-V$_{DLM}$ setup is about 1.5 m (see Chapter 2), with the depth of maximum weighting at ~0.5m. The data from the EMI instrument is transmitted serially through a 9-socket DB-9 connector and was acquired simultaneously with the GPS data using a handheld geographic information system (HGIS, StarPal Inc., Fort Collins, CO) program inside an Allegro CX handheld field computer (Juniper Systems,
Logan, UT). In a previous study we tried using a Geonics EM-38, but the required calibration procedure to null out the magnetic susceptibility circuit proved to result in inconsistent readings at low \( EC_a \) values (< 20 mS m\(^{-1}\)). The DUALEM-1S only measures \( EC_a \) and comes with factory set calibration, resulting in stable, consistent readings in low \( EC_a \) soils.

**Mapping**

The EMI instrument was turned on for 30 minutes before mapping, which was usually carried out early in the morning or in the evening, to avoid temperature drift effects on the instrument (see Chapter 2). The EMI instrument was held ~10 cm above ground while traversing the field by walking in rows spaced 3m apart (See Fig. 2B). The EMI mapping process required ~45 minutes with \( EC_a \) data being collected every second. The field was mapped 30 times total in summer/fall 2006 and 2007.

Maps were selected from six different days to cover a range of field moisture regimes as recorded in the control plot. The volumetric water content (\( \theta_v \)) ranged from a low of 0.11 (September 21, 2007) to a high of 0.23 (October 7, 2006). Intermediate water-content mapping days had the following \( \theta_v \): 0.13 (October 15, 2007); 0.16 (July 9, 2006); 0.18 (September 28, 2006); and 0.20 (September 26, 2006).

In order to reduce the effect of diurnal temperature fluctuations, the \( EC_a \) data for each day were corrected to a standard temperature of 25°C. The temperature corrected \( EC_a \) data were then checked for continuity and anomalous values using a time-series view of the data. Anomalous values can be caused by buried metal fragments, wires, pipes, etc. These were identified and removed from the data set as a quality control measure.
**Data Analysis**

We carried out exploratory data analysis to produce basic statistics and histograms for each mapping event. The quality controlled EC$_a$ data were normal score transformed using S-GeMS (Remy, 2005) to prepare the data for a kriging process. The field geometry was then subdivided into 2500 blocks of 1-m$^2$ area representing the support area of the EMI instrument. The data was kriged using VESPER (Walter et al., 2001) and then returned to S-GeMS to be back transformed. Temporal stability analysis was then applied to the six EC$_a$ maps. Since our support area is a 1-m$^2$ block, each map was divided into 2500 zones and the relative difference of each zone was calculated for each mapping event. The relative differences for each zone were then averaged across the six mapping events (mean relative difference) and ranked in ascending order.

**RESULTS AND DISCUSSION**

The six selected mapping days representing different volumetric water contents were used to produce field scale EC$_a$ maps presented in Figure 3-3. The maps show the EC$_a$ of the field at varying water content with each color gradation on the map representing an 8 percentile of the data, with the lightest color representing low EC$_a$ and the darkest color representing high EC$_a$ values. The average EC$_a$ of the field for the each volumetric water content is shown in Figure 3-3 and ranged from 7.60 mS m$^{-1}$ at a $\theta_v$ of 0.11 m$^3$m$^{-3}$ to 14.7 mS m$^{-1}$ for the highest water content of 0.23 m$^3$m$^{-3}$.

Visual inspection of the figures shows the low EC$_a$ area corresponding with the general location of the gravel lens and a higher EC$_a$ region to the north. It is also
noticeable that the pattern around the low EC<sub>a</sub> area changes with water content. The map in Figure 3E shows the least consistent pattern. The EC<sub>a</sub> was measured at the end of a rainfall event and we interpret the pattern to indicate the redistribution of water changing the soil EC<sub>a</sub> as the field is mapped. This indicates that mapping should be avoided during or immediately following rainfall events when rapid changes in EC<sub>a</sub> may occur with wetting.

Further analysis of the data was conducted using the coefficient of variation (CV - the ratio of the standard deviation to the average EC<sub>a</sub> of the field). This tended to be lowest at the low and high water contents (Fig 3-3 A, B, and F) and highest at the somewhat intermediate water contents (Fig 3-3 C, D, and E). This perhaps indicates the greatest variation of information can be derived from a somewhat intermediate water content, as will be discussed below.

Box plots are presented in Figure 3-4 and show the EC<sub>a</sub> distribution for each mapping event as the volumetric water content increased. A clear increase in the field average EC<sub>a</sub> is observed as a function of water content. The lowest interquartile range (IQR, Q3-Q1) of 1.23 mS m<sup>-1</sup> was observed at the lowest θ<sub>v</sub> of 0.11 and the highest IQR of 2.75 mS m<sup>-1</sup> was observed at the highest θ<sub>v</sub> of 0.23.

Spearman’s rank correlation coefficient (r<sub>s</sub>) was used to get a quantitative measure of the time stability of spatial locations between different mapping days (Table 3-1). From Table 1 the three wetter days of mapping (θ<sub>v</sub> of 0.18, 0.20 and 0.23) have relatively high Spearman’s rank correlation coefficients amongst them. The highest occurs between mapping events with θ<sub>v</sub> of 0.18 and 0.20 with r<sub>s</sub> = 0.92. The two driest days of mapping
(water contents of 0.11, 0.13) have the second highest $r_s$ in the table at 0.89. The wet and dry mapping days that have the highest correlation coefficients amongst them are those mapped a few days apart. The mapping events at water contents just below field capacity (e.g. $\theta_v = 0.16$ and $\theta_v = 0.20$) are the least correlated with the other mapping events.

The relative differences for each zone were averaged across the six mapping events (mean relative difference) and ranked in ascending order to produce Figure 3-5A. The lowest ranked spatial location (zone) is 27% below the averaged mean $EC_a$ of the six mapping events, while the highest ranked zone is 18% above it. We interpreted the inflexion points as indicating transition zones between soil units, representing boundary delineations to classify the field into three regions (Figure 3-5B). The regions were classified using the following ranges of mean relative difference percentages: Region 1 (lowest conductivity area), -27 to -11%; Region 2, -11 to 5%; and Region 3 (highest conductivity area), 5 to 18%.

Ground truthing was conducted to determine observable differences in these regions. The two soils described initially are consistent with Regions 1 and 3. Selected morphological properties of the soils are illustrated in Figure 3-6. The Millville pedon (coarse-silty, carbonatic, mesic Typic Haploxerolls) of the control plot (Figure 3-6A) represents a typical pedon of the gravel-free, silt-loam dominated Millville series found in Region 3. The pedon with the gravel lens (coarse-loamy, carbonatic, mesic Entic Haploxerolls) typical of Region 1 (Figure 3-6B) has a substantial amount of gravel throughout the upper 65 cm, with a gravel lens (80% gravel by volume) from 45 to 65 cm.
Core samples representative of the three zones were taken in 30-cm increments. In Region 1 where we expected the gravelly soil, the coring device was only able to penetrate up to a depth of about 40 cm until impeded by the gravel, so only one core was sampled. In Region 2 the coring device was able to penetrate deeper, going to depths of between 70 and 85 cm, with the depth increasing with distance from Region 1. Three cores were sampled in Region 2. In Region 3, five cores were taken to the extent of the device (90 cm), indicating essentially no gravel in this zone.

Each 30-cm core sample was homogenized and analyzed for particle size distribution using the hydrometer method (Gee and Bauder, 1986). In addition to the clay percentage, the percentage of fine particles (silt + clay) was determined due to its importance in the water holding capacity of the soil. Region 2 had an average clay percentage of 11.9 ± 1.09%, whereas Region 3 had an average clay percentage of 12.9 ± 1.82%. We did not find a statistically significant difference between the average clay percentages of Regions 2 and 3. However, the average fine particle percentages in Regions 2 and 3 were 50.5 ±4.39% and 54.6 ±4.09%, respectively. We were able to reject the null hypothesis of equal means of fine particle percentage for both regions at the 5% significance level (p=0.023) using a two sample t-test. The test was repeated with the nonparametric Wilcoxon rank sum test, and we were able to ascertain at the 5% significance level (p=0.036) that the medians of the fine particle percentage were different between Regions 2 and 3.

We interpret Region 1 as the gravel lens, which pinches out in Region 2, giving way to the homogeneous Millville silt-loam in Region 3. Region 1 is consistent with a
relict high energy channel of the alluvial fan. As the energy of the channel subsided, finer
textured material was deposited forming the present Millville Series soil. We can also see
from our textural delineation map (Figure 3-5B) that the coarser texture material was also
spreading at the edge of the high energy channel depositing a limited amount of gravel
around the surrounding area until pinching out. The spread of the gravel was predisposed
towards the south to Region 2 where our depth of coring was limited and the fine particle
percentage is lower compared to Region 3.

Clearly, a multi-mapping strategy provides useful information for delineating soil
textural boundaries without the extra work physical calibration requires. However,
repeated mapping cannot always be achieved and so a pertinent question is, 'for soils with
low electrical contrasts, like non-saline soils, is there an optimum water content for
determining underlying spatial patterns of soil texture?' In order to attempt to answer this
question we examine the histograms of the kriged maps (Figure 3-7). We focus on the
driest mapping event (water content of 0.11), wettest mapping event (water content of
0.23), and a mapping event in between with a water content of 0.16 (medium). The
histogram for $\theta_v = 0.16$, shows 3 strong peaks, these appear to collapse and merge at the
high and low water contents. This may indicate that the strongest contrast occurs at water
contents just below field capacity (~0.21).

If physically or economically limited to one mapping event, the strongest
texturally induced EC_a differences in the Millville soil were observed below field
capacity. This point ($\theta_v = 0.16$) has the highest coefficient of variation, 16 % (Figure 3-
3), it is the least correlated with the other maps (Table 3-1), and it exhibits a multimodal histogram with distinct peaks (Figure 3-7).

The repeated EMI mapping of low EC<sub>c</sub> soils at varying water content reveals the textural patterns of the subsurface as demonstrated in this study. The fact that the range of EC<sub>a</sub> in this research was only about 10 mS m<sup>-1</sup> makes the adaptation of this methodology into areas with a larger EC<sub>a</sub> range more informative. Thus repeated EMI mapping can be useful in soil surveys to delineate areas with heterogeneous soils as well as in better defining transition zones between soil units. The methodology should be considered a tremendous benefit in the arsenal of tools used by the soil surveyor, especially for site-specific soil maps. All geophysical techniques exploit contrasts in target properties and as such require careful interpretation. The methodology could be useful in precision agriculture in demarcating productivity and management zones for improved utilization of resources and better yield without the need for extensive calibration. The methodology could also be used to improve sampling schemes, especially in pristine environments, by providing an extra layer of information on soil variability and determining locations where maximum or minimum change occurs. This information could be very helpful for the potential placement of monitoring equipment, sensors and observation nodes for monitoring soil hydrological processes in situ.

**CONCLUSIONS**

Spatial variability of soil properties presents difficulty in capturing the heterogeneity without sampling exhaustively and becoming overwhelmed with data
analysis and losing site of the dominant processes. In this study we developed a procedure to non-invasively map field-scale soil textural patterns by separating the EMI response due to water content variation from static textural properties. We collected six geo-referenced EC$_a$ surveys at volumetric water contents ranging from 0.11 to 0.23 of a 50 × 50 m agricultural field. We used block kriging to predict at unsampled areas to produce EC$_a$ maps at 1-m block resolution. Temporal stability analysis was then applied on the six EC$_a$ maps and the field was divided into three regions. Subsequent ground truthing confirmed that the lowest conductivity region was associated with a relict high energy channel that deposited coarser materials (gravel) as the soil parent material. This non-invasive mapping approach has the potential to reveal the spatial distribution of time-invariant subsurface properties using repeated EMI surveys, especially when taken over a range of field soil moisture levels. These maps are informative for modeling and experimental design purposes in soil science, ecology and hydrology, as well as in agricultural applications.

REFERENCES


Table 3-1 Spearman’s Rank Correlation coefficient between the six mapping events at varying volumetric water content, $\theta_v$.

<table>
<thead>
<tr>
<th>Volumetric Water Content</th>
<th>$\theta_v = 0.11$</th>
<th>$\theta_v = 0.13$</th>
<th>$\theta_v = 0.16$</th>
<th>$\theta_v = 0.18$</th>
<th>$\theta_v = 0.20$</th>
<th>$\theta_v = 0.23$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\theta_v = 0.11$</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\theta_v = 0.13$</td>
<td>0.89</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\theta_v = 0.16$</td>
<td>0.79</td>
<td>0.57</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\theta_v = 0.18$</td>
<td>0.69</td>
<td>0.79</td>
<td>0.54</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\theta_v = 0.20$</td>
<td>0.54</td>
<td>0.68</td>
<td>0.43</td>
<td>0.92</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>$\theta_v = 0.23$</td>
<td>0.78</td>
<td>0.72</td>
<td>0.84</td>
<td>0.86</td>
<td>0.77</td>
<td>1</td>
</tr>
</tbody>
</table>
Fig. 3-1. Normal Score Transformation ($\varphi$) of A) the skewed cumulative distribution function (CDF), $F(z)$, from July 9, 2006 EC$_a$ mapping event into B) a normal CDF $G(y)$. 
Fig. 3-2. A) Hillshade image showing the location of the study area (white box) on the distal portion of the alluvial fan (outlined with dotted line) deposited by streams draining Green Canyon (white line), and B) the 50x50m field showing the EMI survey route (dotted line), the general location of the gravel lens (cross-hatch), and locations of the two soils – pits 1 and 2 - described (white boxes).
Fig. 3-3. Block kriged EC\textsubscript{a} maps of the field at varying water content with each shade gradation representing 8 percentile of the data, with the lightest color representing low EC\textsubscript{a} and the darkest color representing high EC\textsubscript{a} values. The general location of the gravel area is inside the dashed line enclosure.
Fig. 3-4. Box plots showing the ECₐ distribution of each mapping event as a function of volumetric water content. The box plots give the 25 (Q1), 50(Q2) and 75(Q3) percentile of the data in the box as well as the 5 and 95 percentile of the data at the whiskers.
Fig. 3-5. Temporal stability analysis – (A) the mean relative difference (%) of the spatial blocks ranked in ascending order and (B), a map of the mean relative difference delineated into 3 regions according to the inflexion points of the mean relative difference graph.
Fig. 3-6. Selected morphological properties of soils described at the Millville control soil representative of Region 3 (A) and the soil with gravelly horizons representative of Region 1 (B), pits 1 and 2 respectively on figure 2. Colors are for moist soil; gravel volume was estimated visually in the field; and clay concentration was estimated by feel.
Fig. 3-7. Histograms of EC$_a$ at $\theta_v = 0.11$ (solid line); $\theta_v = 0.23$ (dashed line); and, $\theta_v = 0.16$ (dotted line) field water content conditions.
CHAPTER 4
GEOPHYSICAL IMAGING OF WATERSHED SUBSURFACE PATTERNS AND PREDICTION OF SOIL TEXTURE AND WATER HOLDING CAPACITY

ABSTRACT

The spatial distribution of subsurface soil textural properties across the landscape, is an important control on the hydrological and ecological function of a watershed. Traditional methods of mapping soils involving subjective assignment of soil boundaries are inadequate for studies requiring a quantitative assessment of the landscape and its subsurface connectivity and storage capacity. Geophysical methods such as electromagnetic induction (EMI) provide the possibility of obtaining high resolution images across a landscape to identify subtle changes in subsurface soil patterns. In this work we show how EMI can be used to image the subsurface of a ~38 ha watershed. We present an imaging approach using kriging to interpolate, and Sequential Gaussian Simulation (SGS) to estimate the uncertainty in the maps. We also explore the idea of difference EC$_a$ mapping to try and exploit changes in soil moisture to identify more hydrologically active locations. In addition we used a digital elevation model to identify flow paths and compare these with the EC$_a$ measurement as a function of distance. Finally we perform a more traditional calibration of EC$_a$ with clay percentage across the watershed and determine soil water holding capacity (SWHC). The values of SWHC

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range from 0.07 to 0.22 m\(^3\)m\(^{-3}\) across the watershed, which contrast to the uniform value of 0.13 derived from the traditional soil survey maps. Additional work is needed to appropriately interpret and incorporate EMI data into hydrological studies, however, we argue that there is considerable merit in identifying subsurface soil patterns from these geophysical images.

**INTRODUCTION**

Hydrological research is at somewhat of an impasse with many advanced models relying on multi-parameter calibration data. Limitations in the availability of relevant, spatially exhaustive measurements, hinders the advance of our hydrological understanding and description of watershed scale processes. As a result many hydrologists are reflecting on the approaches used and trying to develop alternative ways that focus on the diagnosis of underlying patterns, e.g. soils, vegetation, etc. (McDonnell et al., 2007). This dominant processes concept (Sivakumar, 2004) aims to identify fundamental patterns and controls on the hydrological processes operating in a watershed. It seeks to develop new modeling approaches to describe hydrological response (McDonnell et al., 2007). A major constraint to advancing the science is a lack of quantitative spatial data, identifying subsurface watershed soil patterns that can be used to constrain, test, or even conceptualize models and their frameworks at the watershed scale. In the same way that many hydrological modelers are exploring new approaches, so many scientists with an emphasis on measurement methods are exploring new technologies that can provide quantitative data of value to the hydrological sciences.
Exciting new technologies include the use of distributed temperature sensing (Selker et. al., 2006), Lidar surface mapping (Lane and Chandler, 2003), and Lidar vapor mapping (Cooper et al., 2000). In addition, there is renewed interest in geophysical methods, through the emerging discipline of Hydrogeophysics (Rubin and Hubbard, 2005; Robinson et al., 2008b).

Hydrogeophysics provides a useful tool for obtaining spatial data, with regard to earth properties, that are related to important hydrological parameters, and may be used to constrain hydrological modeling efforts. However, issues such as non-uniqueness of the signal response, scale of measurement and uncertainty are topics that need ongoing research (Rubin and Hubbard, 2005). Examples of recent applications of geophysics for the very near surface include, exploiting magnetic properties to identify fault networks in sedimentary basins that will impact surface and ground water flow (Grauch and Millegan, 1998). The use of delay time response of high frequency electromagnetic (EM) waves to image changes in water table elevation (Hyndman and Tronicke, 2005); exploiting the electrical resistivity properties of the unsaturated zone to monitor snowmelt and seasonal changes in soil moisture (Daniels et al., 2005); and using electrical properties, such as EM wave propagation time, to infer water content (Ferré et al., 2005; Huisman et al., 2003; Robinson et al., 2008c), on the assumption that the propagation time is controlled by the dielectric properties of the porous media, which are in turn controlled by the vadose zone water content.

Electromagnetic induction is a technique, originally developed for the oil industry and well logging, which has been exploited ~ 25 yrs in soils research to identify soil
salinity (Rhoades et al., 1999; Hendrickx and Kachanoski, 2002). However, it’s only in
the more recent past that hydrologists have begun to consider its utility (Kachanoski and
de Jong, 1988; Sheets and Hendrickx, 1995; Sherlock and McDonnell, 2003). The
application of EMI to hydrology has been somewhat limited, this most likely reflects the
fact that measurements are easily made but less easily interpreted. A firm understanding
of soil properties affecting electromagnetic field behavior is helpful in understanding
when EMI can be applied, as it is not suitable for all circumstances. Like all geophysical
methods, EMI exploits contrasts in soil geophysical response, in this case electrical, to
estimate soil textural (Doolittle et al., 1994; Triantafilis et al., 2001; Triantafilis and
Lesch, 2005) and hydrologic patterns (Sherlock and McDonnell, 2003). Research has
shown that the method can be used to estimate water content in soils (Sheets and
Hendrickx, 1995), with the caveat that this is under circumstances where the differences
in water content lead to measurable differences in soil electrical properties; this is
unlikely to be the case in organic soil for instance.

The traditional interpretation of EMI measurements is to try and produce
calibrated maps of soil salinity or texture, and several procedures have been described
(Lesch et al., 1995a, 1995b). Field-scale studies are beginning to explore alternative
methods of interpreting the data, and recognize the important contribution that EMI can
make to observing soil spatial variability and the identification of field-scale
heterogeneities (Corwin and Lesch, 2005). Sherlock and McDonnell (2003) applied this
approach to hillslope studies and argued for the use of ‘soft data’ in helping to interpret
subsurface patterns.
The aim of this research was to present and test an EMI mapping procedure for an entire watershed in order to delineate boundaries and spatial patterns in the subsurface as part of a broader ecohydrological study that focused on the difference between meadow grass and shrub plant communities. Furthermore, to compare this with NRCS soil survey maps of the watershed. The EMI mapping provides an opportunity to compare the quantitative subsurface geophysical image with the more qualitative soil survey interpretation based on landscape and vegetation patterns. Difference mapping, wet and dry, is used to identify areas associated with “change” which might be interpreted in light of hydrological processes. In addition we create a texture map of the watershed based on the EMI response surface and soil sampling. Values of soil water holding capacity are interpreted from the map and compared with the traditional soil survey data.

**MATERIALS AND METHODS**

**Study Area**

The Reynolds Mountain East (RME, 43° 04' N and 116° 45' W) study area (Figure 1) encompassing ~38 hectares is located on the south eastern tip of the larger 239 km² USDA-Reynolds Creek Experimental Watershed (RCEW) in the Owyhee Mountains near Boise, Idaho, USA. The RME study area is monitored at, 5 meteorological measurement stations, a snow course, soil temperature and soil moisture monitoring locations, precipitation stations, and a weir (Slaughter et al., 2001; Marks et al., 2008).

The RME, a small perennial headwater catchment, ranges in elevation from 2010 m to 2140 m and is typical of a semi-arid rangeland ecosystem with some steep slopes (up to 40%) and some shallow weakly developed soils (Seyfried et. al., 2001). The soil
survey map identifies the central woody area, and the north western part of the catchment, as the Parkay-Dehana (Fine-Loamy, Mixed, Superactive Pachic Argicryolls) association and the rest of the watershed as the Parkay-Bergar (Loamy-Skeletal, Mixed, Superactive Pachic Argicryolls) complex (Figure 4-1). The parent material of the soils is comprised of basalt and latite, and rocky outcroppings can be seen close to the ridges. The soil texture ranges from fine loam to clay and the clay percentage increases in proportion with depth towards fractured bedrock – the soil depth exceeds 3m under some of the woodland communities (Grant et al., 2004). The average annual precipitation for RME is about 900 mm and most of it is received in the winter months as snow between November and April. Snowfall which accounts for 75% of the precipitation is affected by wind drifts which contribute to the unevenly distributed infiltration of water into the soil (Marks et al., 2001).

The vegetation at RME is typical of higher elevations and consists of forest and alpine communities. Big Sagebrush (Artemesia tridentata) and grassland communities dominate most of the catchment, with a mixed dense forest in the middle consisting of Douglas-fir (Pseudotsugua menziesii) and Quaking Aspen (Populus Tremuloides). There are patches of snowbrush (Ceanothus Velutinus) and willows (Salix sp.) line the edges of the riparian zone (Grant et al., 2004; Robinson et al., 2008a).

**Mapping**

Apparent electrical conductivity (ECₐ) is a proxy for subsurface physical properties and provides a measure of charge mobility due to the application of an electric field. It is defined as the ratio between current density (J, A m⁻²) and electrical field (E, V m⁻¹) according to Ohm’s law (Paul, 2004), with a unit of milli-Siemens per meter (mS m⁻¹).
An EMI system transmits a low frequency electromagnetic field into the subsurface without the need to establish contact with the ground. The alternating magnetic field in the subsurface in turn induces secondary current loops in proportion to the subsurface electrical conductivity. These create secondary magnetic field loops and the instrument measures the superposition of the combined primary and secondary fields (McNeill, 1980; Chapter 2). This non-invasive technique is appropriate for field scale measurement due to its rapid response, ease of integration into mobile vehicular measuring platforms and nondestructive / non-contact requirements.

Georeferenced ECₐ measurements were taken non-invasively using the DUALEM-1S (Dualem, Milton, ON Canada) ground conductivity instrument along with a Trimble (Trimble, Sunnyvale, CA) ProXT GPS unit. The electromagnetic induction sensor provides a versatile and robust field instrument for determining bulk soil electrical conductivity. Electrical sensors are particularly suited to soil studies because the electrical conductivity of the earth is highly dependent on the electrical conductivity of the clay percentage, soil solution and water content (Friedman, 2005). The depth of exploration (DOE) for the vertical-vertical dipole setup (transmitter-receiver separation of 1 m) of the instrument is about 1.5 m (McNeill, 1980). However, Callegary et al. (2007) have shown that in soils with conductivity that range up to 100 mS m⁻¹ the DOE is reduced to less than 1 m. The EMI instrument was held ~40 cm above ground while traversing the watershed and this means that the effective DOE for the instrument was ~60 cm and the measurement volume was ~0.6 m³. The georeferenced ECₐ data was acquired using a handheld geographic information system (HGIS, StarPal Inc., Fort
Collins, CO) program inside an Allegro CX handheld field computer (Juniper Systems, Logan, UT).

The EMI instrument was turned on for 30 minutes for instrument stabilization before mapping the RME catchment on July 12, 2006 and October 27, 2007. The 2006 mapping was conducted a month after the melting of the snow and subsequent infiltration, leaving the ground saturated prior to ET losses by vegetation. In contrast the 2007 mapping was done after the root zone soil moisture was depleted over the summer; some light rains in the weeks prior to mapping wetted the top part of the soil. Data from a soil moisture monitoring location in an aspen grove gives volumetric water content ($\theta_v$) of 0.35 at the depth of 30 cm for both mapping days. At a deeper depth, the soil was much wetter for the 2006 mapping with $\theta_v$ of 0.40 and 0.59 for depths of 52 and 72 cm, respectively, while the 2007 mapping date had $\theta_v$ of 0.22 and 0.26 for depths of 52 and 72 cm, respectively. Simultaneous measurements of the soil EC$_a$ at 30 and 52 cm were comparable between mapping events; 0.05 S m$^{-1}$ at 30 cm for both mapping events and 0.07 and 0.06 S m$^{-1}$ at 52 cm for 2006 and 2007 mapping events, respectively. In the dense woody areas, the GPS signal was getting weak and we used the i.Trek M3 (i.Trek, Pasadena, CA) GPS unit with the SiRF III chipset with its improved signal reception under the canopy. The EMI mapping process required a full day with EC$_a$ data being collected every second. The EC$_a$ data were then checked for continuity and anomalous values using a time-series view of the data. Anomalous values (4 % of the original data), which can be caused by buried metal fragments, wires, pipes, etc., were identified and removed from the data set as a quality control measure.
Geostatistics

Spatial prediction

Kriging relies on the underlying spatial structure of a measured variable in order to predict its value at unsampled locations (Goovaerts, 1999; Webster and Oliver, 2001). Let \( z(u_\alpha), \alpha = 1,2,...,n \), being a realization of RV \( Z(u_\alpha) \), describe the set of \( n \) EC\_a values measured in the watershed. Most prediction methods, including kriging, average the weighted values of the adjacent sampled values, \( z(u_\alpha) \), in order to predict the variable, \( z^*(u) \), at an unsampled point.

\[
z^*(u) = \sum_{\alpha=1}^{n} \lambda_\alpha z(u_\alpha)
\]

[1]

The kriging estimator is given as the best linear unbiased estimator (BLUE) and thus kriging weights, \( \lambda_\alpha \), are determined by requiring unbiasedness and minimum estimation variance. The spatial dependence of the process, represented in the residuals of a generalized least-squares regression equation, is solved when:

\[
\lambda_\alpha = C^{-1}c(u)
\]

[2]

where \( C \) is the matrix of covariances, \( C(u_\alpha,u) \), between all possible pairs of the \( n \) sample sites and \( c(u) \) is a column vector of covariances between the prediction point and each of the \( n \) sample sites.

In order to solve for \( \lambda_\alpha \) we need to evaluate the matrix of covariances \( C \), which can be done using a semivariogram function, written:

\[
\gamma(h) = \frac{1}{2N(h)} \sum_{\alpha=1}^{N(h)} [z(u_\alpha) - z(u_\alpha + h)]^2
\]

[3]
where the function computes the average squared differences of the values of the random variable at a vector of data pairs $u_\alpha$ and $u_\alpha + h$, where $N(h)$ is a number of data pairs within a given class of distance. A parametric model is used to describe the experimental semivariogram to provide a continuous, positive and smooth description of the covariance matrix, $C$.

Block kriging extends the above method from a point estimation of a spatially continuous variable to the average value over a small area or block (Deutsch and Journel, 1998). This is useful when the support block of a physical measurement is beyond a point as in EMI measurements.

Data transformation using the normal score procedure

The prediction of a property of interest at unsampled areas using kriging requires the data to be normally distributed, since a normal distribution is completely defined by its mean and covariance function to establish its spatial distribution (Webster and Oliver, 2001). The normal score transform is useful in normalizing many environmental variables that have non-uniform distributions or that may be positively skewed, providing a normal distribution (Goovaerts, 1997). The normal score transform function is derived by matching the original skewed cumulative distribution function (cdf) to a standard normal cdf. Let a random function (RF) $Z(u)$ consist of a set of usually dependent random variables (RV) $Z(u_\alpha), \alpha = 1,2, \ldots n$ for each location vector $u_\alpha$ in the study area. Then the transform, $\phi(.)$, that takes any RF $Z(u)$ with cdf $F(z)$ to an RF $Y(u)$ with a standard Gaussian cdf $G(y)$ is given as

$$Y(u) = \phi(Z(u)) = G^{-1}[F(Z(u))]$$  \[4\]
where $G^{-1}(.)$ is the inverse Gaussian cdf of the random function $Y(u)$ (Goovaerts, 1997).

**Sequential Gaussian Simulation (SGSIM)**

In any prediction process, quantifying the uncertainty of the estimate is important to the end user. Kriging, which gives the minimum local error variance in the generalized least square sense, is affected by a smoothing of the local variance of the attribute being predicted. Even though the kriging variance quantifies the quality of a prediction, it is independent of the data values and assesses only the uncertainty of the data configuration, i.e., the spatial distribution of sampled data (Deutsch and Journel, 1998; Goovaerts, 1999).

The spatial variability of the attribute (e.g. EC$_a$) being predicted can be better captured from the data using the sequential Gaussian simulation method (SGSIM) (Goovaerts, 1997). Conditional simulation or stochastic imaging generates equally probable realizations of the property being studied in order to better quantify the uncertainty of the property at unsampled areas. Simulation focuses on honoring the data values while replicating the statistics of the data distribution and the variogram model (Goovaerts, 1999).

In a kriging process, for each node a mean and variance is estimated thus the variable at the node can be represented as a Gaussian random variable. While kriging chooses the mean as an estimate of the node, SGSIM chooses the value of the node randomly from the Gaussian distribution.

SGSIM can be implemented on each node of the prediction grid using the following algorithm (Deutsch and Journel, 1998):
1) We first define a random path that visits each node of the grid once. At each node \( u_\alpha \), a specified number of neighboring conditioning data including both original data and previously simulated grid node values are retained.

2) We then use kriging with a normal score variogram model to determine the parameters (mean and variance) of the conditional cdf of the RF \( Z(u) \) at location \( u_\alpha \).

3) A simulated value \( z^{(l)}(u_\alpha) \) is chosen randomly from the conditional cdf.

4) The simulated value \( z^{(l)}(u_\alpha) \) is added to the data set.

5) The above steps are repeated until all nodes are simulated.

**Channel Network Extraction**

Techniques that extract channel networks from digital elevation models (DEM) have been used successfully to delineate stream networks (Tarboton et al., 1991). The DEM is first smoothed by locally filling spurious depressions to ensure that all pixels flow to a neighbor that will eventually drain to lower elevation. Flow directions are then evaluated for each pixel in order to calculate the number of upstream pixels that flow into each pixel. Those pixels that have accumulation areas exceeding the threshold of 15000 m\(^2\) (150 pixels) were then delineated as part of a channel network.

**Calibration Site Selection**

The spatial site selection algorithm in the ESAP software package (Lesch et al., 2000) was used in order to pick out twenty calibration sites where soil was sampled for subsequent lab analysis. The selection algorithm that uses response surface methodology
(RSM) was developed by Lesch et al. (1995b) to predict field scale soil salinity from $\text{EC}_a$ survey data using multiple linear regression (MLR) models and a limited quantity of calibration samples. We adopted the site-selection technique to predict field-scale clay percentage due to the high correlation between soil textural properties and $\text{EC}_a$ in low $\text{EC}_e$ soils such as those found in the study site. The sample correlation between $\text{EC}_a$ and clay percentage for the 2006 mapping were $r^2 = 0.93$, 0.89 and 0.92 for 0 – 30 cm, 30 - 60 cm and 0 – 60 cm depth samples, respectively.

The calibration sites are chosen such that they embody spatially the full surveyed region and that the corresponding $\text{EC}_a$ data at the calibration sites allow efficient evaluation of the MLR parameters. The $\text{EC}_a$ data was first centered and scaled by normalizing by the mean and standard deviation (i.e. mean of 0 and variance of 1) before the data was uncorrelated by applying a principal components analysis. The transformed $\text{EC}_a$ data was then compared to a second-order central composite (CC) response surface design levels (Box and Draper, 1987); the set of sites which are closest to the design levels and spatially cover the survey area adequately, were selected to be the calibration sites (Lesch et al., 1995b).

Soil physical characteristics were determined for the sampling locations down to 60 cm including, water content, texture, electrical conductivity of the soil solution extract ($\text{EC}_e$). Particles larger than 2 mm were removed from samples prior to textural analysis (USDA – NRCS, 1999). Soil texture was determined using hydrometer analysis (Gee and Or, 2002). These properties along with bulk density were input to Rosetta (Schaap, 1999), a pedotransfer function program that computes the vanGenuchten (VG) soil
hydraulic parameters including residual, $\theta_r$, and saturated, $\theta_s$, water contents. The soil water holding capacity was computed as $(\theta_s/2 - \theta_r)$ yielding soil water holding capacity in cm$^3$ cm$^{-3}$. These values were then adjusted for the gravel content (averaging 20% by volume for the samples), estimating the in-situ soil water holding capacity. Stepwise regression was then used to choose from the linear, quadratic, and interaction terms of the calibration sites’ $EC_a$ and spatial coordinates to select the MLR model variables. The most efficient model was that minimizing the prediction sum of square error residuals (PRESS) statistical criteria (Lesch et al., 1995b).

RESULTS AND DISCUSSION

Exploratory Data Analysis

An exploratory univariate data analysis was performed on the georeferenced $EC_a$ data that was collected for the two mapping dates. The data for the 2006 and 2007 data are comparable and have means that are very close; 21.7 and 20.7, respectively. The probability density function (PDF) also shows the similarity between the two data sets collected more than a year apart (Figure 4-2). According to the distribution statistics, the 2006 $EC_a$ survey exhibits higher upper quartile values corresponding to the deep high water holding capacity soils, while the 2007 survey has a higher range of lower quartile values due to drier soils.

Spatial Prediction of $EC_a$

We used semi-varioigram modeling to capture the spatial correlation of the $EC_a$ survey data. An isotropic exponential model with a nugget of 0.02, range of 350 m and a
sill of 1 (normal score transformed data) and a spherical model with a nugget of 0.05, range of 280 m and a sill of 1 were used to perform ordinary block kriging on a 5 x 5 m pixel for the 2006 and 2007 EC\textsubscript{a} surveys, respectively. The longer range and smaller nugget for the moist soil from 2006 is consistent with the findings of Western et al. (1999), who observed the same pattern for measurements of volumetric water content across a small watershed. The kriged maps for the two mapping years, which are partitioned into 6 quantiles (Figures 4-3 a,b), exhibit similar spatial patterns. Both maps show a low EC\textsubscript{a} area on the southwest corner of the watershed and the highest third of the EC\textsubscript{a} values are located in the center, from the south of the watershed to the northwest.

Sequential Gaussian simulation (SGSIM) was used to produce maps of prediction uncertainty for EC\textsubscript{a} such as the standard deviation (SD) in Figures 4-3c and 4-3d by aggregating 50 realizations of the underlying random process. Since SGSIM honors the observed data, the survey routes stand out on the maps with SD values of zero. The low conductivity area on the southwest corner of the watershed has a lower SD for both years (< 7 mS m\textsuperscript{-1}). The standard deviation increases in the high conductivity regions and especially in areas where the distance between survey points is the furthest. Overall, lower values of SD for the 2007 survey are observed and can be attributed to the better EC\textsubscript{a} survey coverage of the watershed.

The difference between “wet” and “dry” predicted EC\textsubscript{a} maps can also be used to study the soil morphology of the catchment. It also helps to identify hydrologically active locations in a qualitative sense, i.e. locations where water may be accumulating or depleting. We subtracted the dry (2007) EC\textsubscript{a} map from the wet (2006) map and examined
the change in EC\(_a\) as a proxy for observing changes in water storage (Figure 4-4a). We interpret the areas with a large positive change to be associated with deep soils that have higher clay percentage and higher water holding capacity, those with little or no change as shallow often more stony soils, while those locations with a high negative change we interpret as soils with the possibility of some ion accumulation (Friedman, 2005). The areas exhibiting the largest changes are consistent with the eastern side of the watershed. These areas are also locations where more vegetative growth is observed and may indicate water use by the trees and shrubs (Figure 4-4b).

**EC\(_a\) and Channel Networks**

Using a 10m DEM, those pixels which received contribution from an upper catchment area of 150 pixels (15,000 m\(^2\)) were designated as being part of a channel network (Figure 4-5a). This DEM derived network can be compared with the surface water channel plotted in Figure 4-1. The DEM network allows the estimation of the expected location of subsurface flow paths according to the surface topography. We then looked at how the average EC\(_a\) of a 5m buffer area varied as the buffer moved away from the channel network (Figure 4-5b). For the 2006 SGSIM map, we observe a constant decline in the average EC\(_a\) up to 50m away from the channel network and subsequent leveling of the average EC\(_a\) for the next 100 m. This is in broad agreement with the concept of soil catena, from which we would expect the fine textured materials to accumulate in downslope positions in the landscape. Given the strong correlation between clay percentage and the EMI measurement, this is strong qualitative evidence that the EMI mapping is picking up the soil textural patterns of the watershed.
**Clay Percentage Map**

A multiple linear regression (MLR) model was used to produce a clay percentage map for the top 0.6 m of the RME watershed (Figure 4-6a). Stepwise linear regression was applied to identify $EC_a$ followed by latitude (Northing) as significant covariates to fit the MLR model. The model is written:

\[
\text{Clay Percentage} = 14.98 + 6.87 \, y + 10.31 \, z
\]  \[5\]

where $y$ and $z$ are the normalized latitude (Northing) coordinate and the normal score transformed $EC_a$ measurements, respectively.

Using these variables as predictors, the proportion of variability in the data that is accounted for by the MLR model was given as $R^2 = 0.86$ and the RMSE of the model was 4.4%. The map was divided into 6 classes corresponding approximately to clay percentage boundaries on the USDA soil textural triangle indicating change in soil textural class. This map can be compared with the soil survey map showing the two soil series mapped for the site (Soil Survey Staff, 2008). The soil survey map classifies both soils as clay loam with ~20% clay (Soil Survey Staff, 2008). Figure 6a indicates that the clay percentage is not uniform and varies from < 10% to > 36%. Hydrological modeling based on the soil survey data would treat the soils as uniform across the entire watershed, in semi-arid environments, where the available water is the limiting factor on biological processes, a texture map would be useful in estimating the amount of biologically available water (Newman et al., 2006). A spatially-detailed texture map can demonstrate the role of soil texture in controlling plant distribution and vegetation structure by
determining the distribution and duration of water storage (Fernandez-Illiescas et al., 2001; Robinson et al., 2008a).

**Soil Water Holding Capacity Map**

Following the procedure outlined in 2.5, a soil water holding capacity map for the top 0.3 m of the RME watershed was generated. Stepwise linear regression was applied to identify EC<sub>a</sub> followed by latitude (Northing) as significant covariates to fit the MLR model. The model is written:

\[
\text{Soil Water Holding Capacity} = 0.110 + 0.021 y + 0.021 z
\]

where \(y\) and \(z\) are the normalized latitude (Northing) coordinate and the normal score transformed EC<sub>a</sub> measurements, respectively.

Using these variables as predictors, the proportion of variability in the data that is accounted for by the MLR model was given as \(R^2 = 0.75\) and the RMSE of the model was 0.01. A detailed map, although non-unique and contingent upon particular calibration sites, of soil water holding capacity is obtained (Figure 4-6b). The map obtained from the conventional approach using water holding capacity available from Web Soil Survey (Soil Survey Staff, 2008) gave a uniform value of 0.13 m<sup>3</sup> m<sup>-3</sup> for the entire watershed. The NRCS soil survey map delineates the site into two similarly textured soils (Figure 4-1), each with a soil water holding capacity of 0.13 m<sup>3</sup> m<sup>-3</sup>. In the detailed map obtained from the EC<sub>a</sub> mapping procedure, the range of SWHC extends from 0.079 to 0.215 m<sup>3</sup> m<sup>-3</sup> across the watershed resulting in an integrated storage capacity for the top 0.3 m of the catchment of 12900 m<sup>3</sup> compared to 14800 m<sup>3</sup> using the generalized NRCS data. In this particular example the soils appear to have been mapped following the vegetation
boundary (Figure 4-1), which in this case is an unsuitable boundary indicator as indicated by the geophysical EMI map (Figure 4-3 a,b). Such spatially-detailed storage maps can be useful in studying the discrepancy between measured hydrographs and model predictions, where average values used for soil moisture and soil hydraulic parameters can lead to large deviations (Merz and Plate, 1997). Accounting for the spatial variability of infiltration properties is important in understanding runoff production (Woolhiser et al., 1996; Michaelides and Wilson, 2007), and the role of organizational patterns of soil moisture on catchment runoff (Merz and Plate, 1997). Such maps will be useful in understanding the effect of the spatial correlation of infiltration patterns in runoff pathways connectivity as well as modeled runoff uncertainty (Michaelides and Wilson, 2007).

Soil mapping is no easy task, and clearly in this instance the geophysical method proves superior for this scale of watershed. However, for larger areas handheld geophysical mapping becomes infeasible, and soil survey maps remain the only current option. However, advances in airborne geophysical methods may provide the option of collecting spatial data over larger areas, especially with new techniques more clearly focused on hydrological applications of geophysics (Robinson et al., 2008b).

**CONCLUSIONS**

Electromagnetic induction mapping is demonstrated to significantly advance our ability to image the subsurface of a small (~38 ha) watershed. The image clearly identifies soil boundaries and soil connectivity. The observed patterns are informative in
a qualitative sense, but we go on to show how the EMI data can be used to provide a more detailed estimate of watershed soil properties than simply using soil survey. The traditional low-level soil survey for the area provides a watershed average soil moisture holding capacity of $0.13 \text{ m}^3\text{m}^{-3}$, a reasonable estimate but one that lacks in the showing the spatial patterns of the soil. The geophysical image captures the soil patterns and their connectivity and provides an area average SWHC of $0.11 \text{ m}^3\text{m}^{-3}$ with a range varying between $0.07$ and $0.21\text{ m}^3\text{m}^{-3}$. Moreover, by differencing EMI maps observed during wet and dry periods we can identify hydrologically active locations. In addition, combining the EMI map with DEM derived flow paths gives insight into the spatial textural structure in relation to distance from a flowpath. The data and its interpretation indicates the usefulness of using geophysics to map small watersheds and opens a new opportunity to combine measurement and modeling approaches to better understand watershed scale hydrological processes.

**REFERENCES**


Fig. 4-1. Air photo of the Reynolds Mountain East (RME) sub-watershed boundary (red line), contour lines in meters (black), perennial stream (white) and soil series delineation (dotted yellow line) from NRCS Soil Survey with soil unit 1 being classified as the Parkay-Dehana association and soil unit 2 as the Parkay-Bergar complex.
Fig. 4-2. Histogram and summary of the distribution statistics of EC$_a$ for the 2006 and 2007 surveys.
Fig. 4-3. Sequential Gaussian simulation (SGSIM) maps aggregated from 50 realizations for a) 2006 and b) 2007 and the respective standard deviation maps (c,d).
Fig. 4-4. Maps of a) 95 percentile difference in EC$_a$ from 2006 to 2007 and b) transparent overlay of the percentage difference in EC$_a$ over an air photo of the watershed.
Fig. 4-5. a) Delineation of channel networks from a 10m DEM with accumulation area threshold of 15000 m² and b) relationship between distance from channel and average EC_a for the 2006 SGSIM map.
Fig. 4-6. a) Kriged clay percentage map and b) water holding capacity map produced from the 2006 EC₃ survey and the NRCS soil delineation line(dashed).
CHAPTER 5
WATERSHED SCALE SOIL TEXTURE AND UNCERTAINTY PREDICTION USING GEOSTATISTICAL APPROACHES INCORPORATING GEOPHYSICAL INFORMATION

ABSTRACT

Soil texture is a key control for the partitioning of precipitation at the soil surface between water infiltrating or running off. Knowledge of the spatial distribution of soil textural properties at the watershed scale is important for understanding spatial patterns of water movement, and in determining soil moisture storage and soil hydraulic transport properties. Capturing the heterogeneous nature of the subsurface without exhaustive and costly sampling presents a significant challenge. Geophysical methods, such as electromagnetic induction (EMI), provide the possibility of obtaining high resolution images across a landscape to identify subtle changes in subsurface properties. In this work we advance the analysis of EMI data to predict both the clay % and its uncertainty across the landscape, using EMI subsurface images from the ~38 ha Reynolds Creek Experimental Watershed near Boise, Idaho. We present an imaging approach using kriging to interpolate, and Sequential Gaussian Simulation (SGSIM) to capture the uncertainty in the maps. We then use the EMI maps as surrogate variables in order to

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4 The material for this chapter is currently in review as: Abdu, H., D.A. Robinson, A. Boucher, and S.B. Jones, Watershed scale soil texture and uncertainty prediction using geostatistical approaches incorporating geophysical information, Water Resour. Res.
predict clay percentage at unsampled locations comparing different kriging approaches that integrate different levels of information such as clay percentage, apparent electrical conductivity ($EC_a$), and spatial location. Our results show that the multivariate estimation methods incorporating the information in the better sampled $EC_a$ data exhibit lower RMSE of estimation. Leave-one-out cross-validation showed that cokriging and regression kriging, integrating $EC_a$ data, were able to improve the RMSE by 7% and 28% respectively, relative to ordinary kriging that used only clay percentage data. Electromagnetic induction measurements provide an important spatial exhaustive layer of information that can improve the quality and resolution of spatial soil property information used in ecohydrological, environmental, and agricultural research.

**INTRODUCTION**

Knowledge of the spatial distribution of soil textural properties in a watershed is fundamental to recognizing and understanding flow-paths (Western et al., 2001), patterns of water movement, and in determining soil moisture storage and soil hydraulic properties (Grayson et al., 2002). Spatial patterns of subsurface textural properties are also important in understanding the space-time links between soils and vegetation in ecohydrological studies (Rodriguez-Iturbe, 2000). Readily available high resolution images of the subsurface will advance the field of catchment hydrology by describing the structure of heterogeneity and by aiding the development, calibration and testing of distributed hydrological models (Grayson et al., 2002). Electromagnetic induction (EMI) imaging has been demonstrated to provide an important tool for imaging subsurface
patterns in small watersheds (see Chapter 4) and linking soils and ecohydrological structure (Robinson et al., 2008).

Limited point-measurements are inadequate in identifying organization of spatial patterns (Western et. al, 1999) and thus exhaustive sampling and costly sample analysis is needed to capture the heterogeneous nature of the subsurface (Western and Grayson, 1998). EMI measurements combine sufficient spacing, extent and support (i.e. scale triplet, Blöschl and Grayson, 2000) to capture the small and large scale variability of the well correlated soil textural properties. Geostatistical methods are often used to interpolate EMI point data to create subsurface images that provide an important insight into the spatial variation of the subsurface (Bourgault et al., 1996). However, the interpretation of the EMI electrical signal response to predict spatial soil properties, and particularly their associated uncertainty, presents a challenge. Lesch et al. (1995a, b) presented a response surface directed sampling and subsequent multiple linear regression to correlate soil properties to the EMI signal response. Multivariate geostatistics is another way of combining a sparsely sampled field data with easily obtained exhaustively measured auxiliary data (Webster and Oliver, 2001). In this work we compare the combination of multivariate kriging and stochastic simulation to estimate both soil properties and uncertainty and identify the best approach to obtain this level of information.

Indirectly measured surrogate variables are usually the preferred choice, in quantifying hard to measure properties, when they can be obtained easily and automatically, and are well related to the property of interest (Blöschl and Grayson,
(2000). Some examples of surrogate variables in measuring soil properties include: apparent dielectric permittivity in determining water content of a volume of soil using time domain reflectometry (TDR, Robinson et al., 2003); the deceleration of neutrons in the soil to determine water content using neutron probes (Evett and Steiner, 1995); and the heat capacity of a volume of soil to measure soil water flux using heat pulse probes (Kluitenberg, 2002).

Apparent electrical conductivity (EC$_a$) is a variable that can be a proxy for subsurface physical properties. EC$_a$ provides a measure of charge mobility due to the application of an electric field. It is defined as the ratio between current density and electrical field according to Ohm’s law, with a unit of milli-Siemens per meter (mS m$^{-1}$) (Paul, 2004). It can be measured using (a) a four electrode array where current is injected into the subsurface and the induced voltage is measured (Rhoades et al., 1999), (b) TDR where the attenuation of the electromagnetic signal at long times is related to EC$_a$ (Robinson et al., 2003) and (c) EMI (Hendrickx and Kachanoski, 2002).

EMI transmits a low frequency (~9 KHz) electromagnetic field into the subsurface, whereby it induces current loops in proportion to the subsurface EC$_a$. The current loops in turn induce secondary magnetic field loops which are picked up by the receiver of the instrument (McNeill, 1980). This non-invasive technique is appropriate for field scale measurement due to its rapid response, ease of integration into mobile vehicular measuring platforms, and nondestructive and non-contact requirements (Hendrickx and Kachanoski, 2002). The EMI sensor is particularly suited to soil studies
because the electrical conductivity of the earth is highly correlated to the electrical conductivity of the soil solution, clay percentage, and water content (Friedman, 2005).

EMI-based EC\textsubscript{a} measurements have been used by researchers attempting to infer different soil properties and characterize a wide range of processes for a host of different applications mostly by correlating signal response with specific variables of interest (Hendrickx and Kachanoski, 2002). Some of the applications include: soil salinity estimation (Corwin and Lesch, 2005), estimating claypan depth (Doolittle et al., 1994); petrocalcic horizon depth (Boettinger et al., 1997); producing field scale textural maps (Triantafilis and Lesch, 2005); and delineation of soil classification zones (Vitharana et al., 2008). In the more recent past hydrologists have also begun to consider EMI's utility for determining water content, soil and hillslope hydrological processes (Kachanoski and de Jong, 1988; Sheets and Hendrickx, 1995; Sherlock and McDonnell, 2003; Robinson et al., 2008). A firm understanding of soil properties affecting electromagnetic field behavior is helpful in understanding when EMI can be applied, as it is not suitable for all circumstances. We have shown previously that EMI surveys are of use in imaging textural spatial patterns only in soils where EC\textsubscript{e} is not a major contributor to the apparent electrical conductivity (see Chapter 4).

Several researchers have used multivariate geostatistics to incorporate better sampled and well correlated secondary data in order to improve the prediction of the primary variable. Some examples include: the incorporation of a digital elevation model (DEM) to better interpolate rainfall from a sparse network of rain gauges (Goovaerts, 2000); the use of elevation, yield and EMI data to better classify soil types (McBratney et
al., 2000); and the use of ECₐ as secondary data to create high resolution soil carbon maps (Simbahan et al., 2006). Triantafilis et al. (2001) have used multivariable kriging with different ancillary variables including ECₐ to predict clay content of an agricultural field; the prediction improving as the transect width decreased. The aim of this research was to present an EMI analysis procedure that goes beyond soil property mapping by also determining the associated uncertainty in the estimate for an entire watershed.

The paper is organized as follows. We first describe the field site, EMI mapping, and the geostatistical analysis methods used in this study. Then we present an exploratory data analysis of the measured patterns of EMI watershed images and textural analysis of the soil samples. We then perform geostatistical analysis on the data: using semivariogram analysis to describe the spatial correlation of the ECₐ, clay percentage and the cross-correlation between ECₐ and clay percentage; and the use of single variable and multivariate kriging to produce clay percentage prediction maps. Leave-one-out cross-validation is used to assess the impact of incorporating the readily available EMI information for predicting clay percentage and a prediction uncertainty map is created using stochastic simulation.
MATERIALS AND METHODS

Study Area

The Reynolds Mountain East (RME, 43° 04' N and 116° 45' W) study area (Figure 5-1) encompassing ~38 hectares is located on the south eastern tip of the larger 239 km² USDA-Reynolds Creek Experimental Watershed (RCEW) in the Owyhee Mountains near Boise, Idaho, USA. The RME study area is monitored at 5 meteorological measurement stations, a snow course, soil temperature and soil moisture monitoring locations, precipitation stations, and a weir (Marks et al., 2008).

The RME watershed is a small perennial headwater catchment, ranging in elevation from 2010 m to 2140 m and is typical of a semi-arid rangeland ecosystem with some steep slopes (up to 40%) and some shallow weakly developed soils (Seyfried et al., 2001). The soil survey map (Soil Survey Staff, 2008) identifies the central woody area, and the north western part of the catchment, as the Parkay-Dehana (Fine-Loamy, Mixed, Superactive Pachic Argicryolls) association and the rest of the watershed as the Parkay-Bergar (Loamy-Skeletal, Mixed, Superactive Pachic Argicryolls) complex (Figure 1). The parent material of the soils is comprised of basalt and latite, and rocky outcroppings can be seen close to the ridges. The soil texture ranges from fine loam to clay and the clay percentage increases in proportion with depth towards fractured bedrock – the soil depth exceeds 3m under some of the woodland communities (Grant et al., 2004). The average annual precipitation for RME is ~900 mm and most of it is received in the winter months as snow between November and April. Snowfall which accounts for 75% of the
precipitation is affected by wind drifts which contribute to the unevenly distributed infiltration of water into the soil (Marks et al., 2008).

The vegetation at RME is typical of higher elevations and consists of forest and alpine communities. Big Sagebrush (*Artemesia tridentata*) and grassland communities dominate most of the catchment, with a mixed dense forest in the middle consisting of Douglas-fir (*Pseudotsugua menziesii*) and Quaking Aspen (*Populus Tremuloides*). There are patches of snowbrush (*Ceanothus Velutinus*) and willows (*Salix sp.* ) line the edges of the riparian zone (Robinson et al., 2008).

**Imaging**

Georeferenced EC$_a$ measurements were taken non-invasively using the DUALEM-1S (Dualem, Milton, ON Canada) ground conductivity instrument along with a Trimble (Trimble, Sunnyvale, CA) ProXT GPS unit. The depth of exploration (DOE) for the vertical-vertical dipole setup (transmitter-receiver separation of 1 m) of the instrument is about 1.5 m (Abdu et al., 2007). However, Callegary et al. (2007) have shown that in soils with conductivity that range up to 100 mS m$^{-1}$ the DOE is attenuated to less than 1 m. The EMI instrument was held ~40 cm above ground while traversing the watershed and this means that the effective DOE for the instrument was ~60 cm. The georeferenced EC$_a$ data was acquired using a handheld geographic information system (HGIS, StarPal Inc., Fort Collins, CO) program inside an Allegro CX handheld field computer (Juniper Systems, Logan, UT).

The spatial site selection algorithm in the ESAP software package (Lesch et al., 2000) was used in order to pick out 72 calibration sites over three mapping seasons where
subsequently soil was sampled for lab analysis. We adopted the site-selection technique to predict field-scale clay percentage due to the high correlation between soil textural properties and \( EC_a \) (see Chapter 4). The calibration sites were chosen such that they spatially embody the full survey region, and so that the corresponding \( EC_a \) data at the calibration sites allow efficient evaluation of the MLR parameters (Box and Draper, 1987). The \( EC_a \) data was first centered and scaled by normalizing by the mean and standard deviation (i.e. mean of 0 and variance of 1) before the data was uncorrelated by applying a principal components analysis. The transformed \( EC_a \) data was then compared to second-order central composite response surface design levels. The set of sites which are closest to the design levels and spatially cover the survey area adequately, were selected to be the calibration sites (Lesch et al., 1995b). Soil physical characteristics were determined for the sampling locations down to 60 cm including: water content, texture, and \( EC_e \). For the textural analysis, organic matter was removed by digestion before the Hydrometer step (Gee and Or, 2002).

**Geostatistics**

**Spatial prediction**

Kriging relies on the underlying spatial structure of a measured variable in order to predict its value at unsampled locations (Goovaerts, 1997). Let \( z(u_\alpha), \alpha = 1,2, \ldots, n \), for each location vector \( u_\alpha \) in the study area, being a realization of random variable (RV) \( Z(u_\alpha) \), describe the set of \( n \) clay percentage values measured in the watershed. Most prediction methods, including ordinary kriging (OK), average the weighted values of the
adjacent sampled values, \( z(u_a) \), in order to predict the variable, \( z^*(u) \), at an unsampled point.

\[
z_{\text{OK}}^*(u) = \sum_{\alpha=1}^{n} \lambda_\alpha z(u_\alpha)
\]

[1]

The kriging estimator is given as the best linear unbiased estimator (BLUE) and thus kriging weights, \( \lambda_\alpha \), are determined by requiring unbiasedness and minimum estimation variance. The spatial dependence of the process, represented in the residuals of a generalized least-squares regression equation, is solved when:

\[
\lambda_\alpha = C^{-1}c(u)
\]

[2]

where \( C \) is the matrix of covariances, \( C(u_\alpha, u_\beta) \), between all possible pairs of the \( n \) sample sites and \( c(u) \) is a column vector of covariances between the prediction point and each of the \( n \) sample sites.

In order to solve for \( \lambda_\alpha \) we need to evaluate the matrix of covariances \( C \), which can be done using a semivariogram function, written:

\[
\gamma_{zz}(h) = \frac{1}{2N(h)} \sum_{\alpha=1}^{N(h)} [z(u_\alpha) - z(u_\alpha + h)]^2
\]

[3]

where \( N(h) \) is the number of pairs of data points distance \( h \) apart.

Ordinary cokriging (CK) extends the above estimation procedure by incorporating a secondary property \( y(u_\beta) \), \( \beta = 1,2, ...m \), being a realization of the RV \( Y(u_\beta) \), the set of \( m \) \( EC_a \) values that are well correlated with the property of interest. Then we can estimate clay percentage at unsampled locations, \( z^*_{\text{CK}}(u) \), using:
where \( m_Z \) and \( m_Y \) are the global means of the clay percentage and \( EC_a \) data, respectively.

The second term of equation 4 corresponds to a rescaling of the secondary variable (\( EC_a \)) to the mean of the primary variable (clay percentage) to ensure unbiased estimation.

The cokriging weights can be solved using the following equations:

\[
\sum_{\alpha=1}^{n(u)} \lambda_{\alpha}^{CK}(u)\gamma_{ZZ}(u_u) + \lambda_{\alpha}^{CK}(u)\gamma_{ZY}(u_u) + \mu^{CK}(u) = \gamma_{ZZ}(u_u), \quad \beta = 1, \ldots, n(u)
\]

\[
\sum_{\alpha=1}^{n(u)} \lambda_{\alpha}^{CK}(u)\gamma_{YZ}(u_u) + \lambda_{\alpha}^{CK}(u)\gamma_{ZY}(0) + \mu^{CK}(u) = \gamma_{YZ}(0), \quad \beta = 1, \ldots, n(u)
\]

\[
\sum_{\alpha=1}^{n(u)} \lambda_{\alpha}^{CK}(u) + \lambda_{\alpha}^{CK}(u) = 1
\]

\( \gamma_{ZZ} \) and \( \gamma_{YY} \) are the direct semivariograms for clay percentage and \( EC_a \), respectively, as modeled from the experimental semivariograms in equation 3, while \( \gamma_{ZY} \) is the cross-semivariogram value between clay percentage and \( EC_a \) and is calculated using:

\[
\gamma_{ZY}(h) = \frac{1}{2N(h)} \sum_{a=1}^{N(h)} [z(u_a) - z(u_a + h)][y(u_a) - y(u_a + h)]
\]

Another kriging variant, regression kriging (RK), also known as kriging with local varying means (Goovaerts, 1997), can also be used to predict clay percentage by incorporating additional information from the \( EC_a \) data. Electromagnetic induction mapping makes it possible to densely sample \( EC_a \) over the watershed and subsequently kriging can be used to create an exhaustive map, where we have estimates of \( EC_a \) values for each pixel on the watershed. In regression kriging, we first use a multiple linear
regression (MLR) model to describe the relationship between the 72 clay percentage samples and the co-located EC\textsubscript{a} measurements, \( z_f(u) = f(y(u)) \). Each pixel of the watershed was then assigned a clay percentage value according to the MLR equation. The 72 residuals of the MLR model (\( r(u) \)), i.e. the difference between the regression estimate and actual measured values, were then used to compute residual values for each pixel using simple kriging (SK). Clay percentage was then calculated by combining the residual and MLR maps to get the RK estimate:

\[
 z^{*}_{RK}(u) = f(y(u)) + \sum_{\alpha=1}^{n(u)} \lambda_{\alpha}^{SK}(u)r(u_{\alpha}) \tag{7}
\]

The weights are solved by:

\[
 \sum_{\alpha=1}^{n(u)} \lambda_{\alpha}^{SK}(u)\gamma_{\text{resid}}(u_{\alpha} - u_{\beta}) = \gamma_{Zz}(u_{\alpha} - u), \ \beta = 1, ..., n(u)
\]

The above kriging methods are just a select few interpolation techniques that can be used to create clay percentage prediction maps. Ordinary kriging makes use of only the clay percentage data, while the multivariate regression kriging and cokriging incorporate the readily available EMI data. Regression kriging, moreover, integrates spatial location information that is not available to the other two methods. The integration of spatial location information can also be attained using kriging with a trend when we only have clay percentage data, and kriging with an external drift (KED) can be used for multivariate cases. Studies have shown the equivalence of regression kriging and KED wherein both methods incorporate clay percentage, EC\textsubscript{a}, and spatial location data (Goovaerts, 1999; Hengl et al., 2007).
We used the normal score transform on our data due to its effectiveness in normalizing many environmental variables that have non-uniform distributions (Goovaerts, 1997). The normal score transform function is derived by matching the original skewed cumulative distribution function (cdf) to a standard normal cdf.

**Sequential Gaussian Simulation (SGSIM)**

In any prediction process, quantifying the uncertainty of the estimate is important to the end user, especially in hydrology. Kriging, which gives the minimum local error variance in the generalized least squares sense, is affected by a smoothing of the local variance of the attribute being predicted. Conditional simulation or stochastic imaging generates equally probable realizations of the property being studied in order to better quantify the uncertainty of the property at unsampled locations. Simulation focuses on honoring the data values while replicating the statistics of the data distribution and the variogram model (Goovaerts, 1999).

In order to implement SGSIM on each node of the prediction grid, we first define a random path that visits each node of the grid once. At each node \( u_\alpha \), a specified number of neighboring conditioning data including both original data and previously simulated grid node values are then retained. We then use kriging with a normal score variogram model to determine the parameters (mean and variance) of the conditional cdf of the RF \( Z(u) \) at location \( u_\alpha \). A simulated value \( z^{(l)}(u_\alpha) \) is then chosen randomly from the conditional cdf and added to the data set (Deutsch and Journel, 1998). The above steps are repeated until all nodes are simulated.
Evaluation of estimation methods

Leave one out cross validation was used to assess the performance of the different prediction methods (Wackernagel, 2003). Each clay percentage value, \(z(u_\alpha)\), is removed from the data set and value \(z^*(u_{[\alpha]})\) is then re-estimated from the remaining n-1 samples (with the inclusion of EC\(_a\) for the multivariable kriging methods) using the different geostatistical algorithms. The comparison criteria are based upon the difference between the true clay percentage value and its estimate, \(z(u_\alpha) - z^*(u_{[\alpha]})\).

The mean error (ME) averages the cross validation errors and is an indicator of apparent bias of the predictor,

\[
ME = \frac{1}{n} \sum_{\alpha=1}^{n} [z(u_\alpha) - z^*(u_{[\alpha]})]
\]  \[8\]

While the root mean square error (RMSE) is a good way of comparing the different predictors.

\[
RMSE = \sqrt{\frac{1}{n} \sum_{\alpha=1}^{n} [z(u_\alpha) - z^*(u_{[\alpha]})]^2}
\]  \[9\]

The geostatistical procedures of normal score transformation, kriging, sequential Gaussian simulation, and subsequent evaluation of the estimation methods was performed with the Stanford Geological Modeling Software (SGeMS; Remy, 2005).
RESULTS AND DISCUSSION

Exploratory Spatial Data Analysis

EC<sub>a</sub> survey data

EMI surveys were conducted in 2005, 2006, and 2007. The electrical conductivity from the 2007 survey ranged from 0.3 to 128 mS m<sup>-1</sup>, the average was 20.7 mS m<sup>-1</sup> with a median of 13.3 mS m<sup>-1</sup> and a standard deviation (SD) of 18.4. The spatial correlation of the EC<sub>a</sub> survey data was described with an isotropic spherical semivariogram model with a nugget of 0.05, range of 280 m and a sill of 1 (normal score transformed data). A watershed EC<sub>a</sub> map was produced using ordinary kriging on a 5 x 5 m pixel grid for the 2007 EC<sub>a</sub> survey (Figure 5-2a). The kriged EC<sub>a</sub> map had a range from 2.5 to 120 mS m<sup>-1</sup>, with a mean of 22.5 mS m<sup>-1</sup>, median of 14.6 mS m<sup>-1</sup> and SD of 19.0. The kriged map which is partitioned into 6 quantiles exhibits a low EC<sub>a</sub> area on the southwest corner of the watershed and the highest third of the EC<sub>a</sub> values are located in the center, from the south of the watershed to the northwest.

Sequential Gaussian simulation (SGSIM) was used to produce a map of prediction uncertainty for EC<sub>a</sub> in Figure 5-2b by aggregating 100 realizations of the underlying random process. Since SGSIM honors the observed data, the survey routes stand out on the maps with SD values of zero. The low conductivity area on the southwest corner of the watershed has a lower SD (< 7 mS m<sup>-1</sup>). The standard deviation increases in the high conductivity regions and especially in areas where the distance between survey points is the furthest.
Clay Percentage Data

The clay percentage from the textural analysis of the soil samples ranged from 2.5 to 46.7, with a mean of 20.7 and SD of 11. The fact that our clay samples were collected over three mapping seasons brought its own complications. We had observed that the EC$_a$ values of the same sampling locations were changing seasonally due to differences brought about by factors such as water content. The effect of water content on EC$_a$ values from a dry to wet season is quite significant with some areas showing a change as high as 30 mS m$^{-1}$ (see Chapter 4). This ruled out the use of combinations of EC$_a$ values from the three mapping seasons. Instead we decided to use EC$_a$ data from only one mapping season in order to remove the seasonal effects of soil moisture. The relative time-invariant character of textural properties makes it possible to use a single season’s EC$_a$ data for comparison with clay percentage collected over three seasons. Thus we chose the 2007 survey to produce a 1m pixel EC$_a$ map of the watershed to better differentiate sampling sites that are close to each other. The EC$_a$ map was then used to obtain the corresponding EC$_a$ values for the 72 sample locations. The EC$_a$ data for the 72 samples ranged from 2.3 to 75 mS m$^{-1}$, with a mean of 32.5 mS m$^{-1}$ and SD of 20. There is a high correlation between EC$_a$ and Clay percentage (Figure 5-3a) with a sample correlation coefficient $r = 0.84$.

A multiple linear regression model was used to predict clay percentage from EC$_a$. The significant covariates to fit the model were identified using step wise linear regression. The model is written:

\[
\text{clay percentage} = 27.3 - 4.45x - 9.75y + 9.13z \]

[10]
where \( x \) and \( y \) are the normalized easting and northing UTM coordinates respectively; and \( z \) is the normal score \( EC_a \) data.

Using the above variables as predictors, the proportion of the variability in the data that is accounted for by the MLR model was given as \( R^2 = 0.73 \) (\( p = 1 \times 10^{-8} \)) and the RMSE of the model was 5.8%. The sample correlation coefficient between observed and modeled clay percentage was 0.86 (Figure 5-3b).

**Clay Percentage Prediction**

**Semivariograms**

The experimental and model normal score semivariograms for the three kriging methods are shown in Figure 5-4. The weighted sum of squares (WSS), which measures the difference between experimental and modeled semivariogram values, was used as a statistical criterion to measure the goodness of the fit. The particular WSS we chose (Cressie, 1985) gives more weight to the first lags by dividing the number of data pairs for each semivariogram value by the squared model value. Since most of the spatial structure is found in data located close to each other, it is appropriate to give more weight to data with smaller spatial separations. Figure 5-4A and B show the experimental and spherical model semivariograms for the 72 clay percentage and \( EC_a \) samples, respectively. Both the clay and \( EC_a \) data were modeled with spherical semivariograms with a sill of 0.85 and a range of 170 m. Figure 5-4C shows the experimental and model cross semivariogram for the combination of the clay and \( EC_a \) data. In order to have a permissible linear model of coregionalization for the cokriging method, the two direct semivariograms for clay and \( EC_a \) as well as their cross semivariogram require fulfilling
the criterion of negative semi-definiteness (Goovaerts, 1997). We can accomplish this requirement with an intrinsic model of coregionalisation, i.e. by using the same shape of model (in this case spherical) and same range distance (i.e. 170 m) for all three semivariograms. The cross semivariogram model (Figure 5-4C) has a sill of 0.6 and a range of 170 m. Figure 5-4D shows the experimental and model semivariograms for the residuals of the clay MLR equation (Equation 10) used in regression kriging. That spherical model has a nugget of 0.3, a sill of 0.75 and a range of 125 m.

**Ordinary kriging**

The three variants of kriging utilizing clay percentage and EC\textsubscript{a} data from 72 samples and the 2007 EC\textsubscript{a} data were then performed. Figure 5-5 shows the clay percentage prediction maps produced using (a) ordinary kriging - OK (b) cokriging – CK and (c) regression kriging – RK. The maps were divided into 6 classes corresponding approximately to clay percentage boundaries on the USDA soil textural triangle indicating change in soil textural class. The OK prediction map (Figure 5-5A), produced from the 72 clay samples and the clay semivariogram (Figure 5-4A), exhibits the typical smoothing effect of kriging and is dependent on the spatial distribution of the clay percentage data. The distribution of the kriged clay percentage data using OK is shown in Figure 5-6; the data ranges from 2.5 to 45.6 % and has a mean of 17.2 and this distribution lies within the range of the field-sampled clay percentage data.
Cokriging

The CK prediction map (Figure 5-5B) was produced using the two direct semivariograms of clay and EC$_a$ (Figures 5-4A and B) and the cross semivariogram (Figure 5-4C) as well as the field collected clay percentage data and the 2007 EC$_a$ survey. The CK prediction map shows the same underlying structure as the OK map but is not as smooth due to the incorporation of the secondary data from the EC$_a$ survey. This incorporation of the EC$_a$ data extends the distribution of the CK clay percentage data beyond the field-sampled clay percentage data; the CK map has a range from 1.6 to 50.9 with a mean of 17.3.

Regression kriging

The RK prediction map (Figure 5-5C) incorporates the linear relationship between clay percentage and EC$_a$ as well as the effect of the distribution of the clay residuals and exhibits a much more heterogeneous map. The clay percentage values for the RK map have a range from 0.60 to 65.8 and a mean of 15.5.

The steps taken to generate the RK map are shown in Figure 5-7. First a clay percentage regression map (Figure 5-7A) was created by applying the MLR model (equation 10) to the EC$_a$ map (Figure 5-3A). We then formed a residual clay percentage map (Figure 5-7B) by simple kriging using the 72 sample residual data and semivariogram (Figure 5-4D). The RK clay percentage map (Figure 5-7C) was then created by adding the clay percentage regression map to the clay percentage residual map, i.e. Figure 5-7C = Figure 5-7A + Figure 5-7B. The clay percentage in the
regression map (Figure 5-7A) is reduced in some areas and augmented in others according to the residual map (Figure 5-7B).

The use of SGSIM for producing equally probable realizations is important in creating a prediction standard deviation map. An uncertainty map (Figure 5-7D) for the RK clay percentage prediction map was produced by taking the standard deviation of 100 equally probable realizations of RK clay percentage maps. We can see from the map that the SD for about 95% of the RK prediction is only between 1 and 3%. Figure 5-8 shows two of the 100 equally probable stochastic realizations of the residuals as produced using SGSIM, and Figure 7B averages 100 of such stochastic realizations. Since stochastic simulation honors the data, we see consistent patterns of positive and negative values in the realizations. Overall, we see positive residual values on the western half of the watershed and negative values on the eastern side (Figure 5-7B). All three kriging methods exhibit high clay percentage values in the south-west part of the watershed and the central part extending from the south-east to the north-west of the watershed, which has previously been shown to be consistent with the watershed topography and flowpaths (see Chapter 4).

**Evaluation of Estimation Methods**

Leave-one-out cross-validation was applied in order to evaluate the effect of incorporating EMI data in the prediction of clay percentage. The three kriging methods produced mean errors of 3.2% in OK, 0.6% in CK and 1.3% in RK, as percentage of the mean. The results show that there are no large apparent biases when using the three
prediction methods, but the multivariate kriging methods which integrated the EMI data into the estimation process performed better than ordinary kriging as expected.

The root mean squared error for OK, CK and RK were 7.6, 7.1 and 5.6, respectively. The inclusion of the easily accessible geophysical EMI data was important in aiding the multivariate methods outperform OK; where CK had a relative improvement of 7% over OK, and RK had a relative improvement of 28% over OK. Regression kriging which incorporates spatial location data as well as ECₐ showed a relative improvement of 21% over CK.

Figure 5-9a shows the relationship between the observed clay percentage values and the clay percentage values as estimated by the three kriging methods using a leave-one-out cross-validation scheme. Regression kriging proves to be the best estimation method as seen by the closeness of the RK points to the 1:1 perfect estimation line. The correlation coefficient between observed and estimated clay percentage for RK was 0.86, while it was 0.73 and 0.74 for OK and CK, respectively.

The goodness of the three kriging methods in estimating each sample clay percentage value using leave one out cross validation was considered by calculating the ratio of the estimation error to the observed value (Figure 5-9b). The closer the ratio to zero, the more accurate the kriging method estimate. Ratios above zero signify overestimation while negative ratios imply underestimation. Most of the samples have an estimation error ratio between -1 and 1 except for a few cases where the observed clay percentage values were just below 10%, suggesting high clay percentage values were better estimated compared with low values. We can also see that the estimation method
that incorporated ECₐ as well as spatial location information in the prediction process (i.e. RK) gave lower estimation error ratios.

We also looked at the effect of the number of samples used for estimation on the RMSE of the three kriging methods by comparing different seasonal combinations of sampling. Figure 5-10 shows the RMSE of the kriging methods relative to ordinary kriging. The multivariate kriging methods that incorporated ECₐ performed better than OK at different sample combinations; with CK showing a relative improvement of 5 to 10% over OK, and a higher relative improvement of 25 to 40% for RK, due to the inclusion of spatial location information. As the number of samples used for estimation are increased, there is a marked improvement in OK estimation due to an improved spatial coverage of the watershed. If we are limited to fewer samples due to time constraints or limited funds, it might be advisable to select RK over the other methods since it can include more information in the prediction process. The limiting factor being enough samples to generate a semivariogram, RK combined with the ESAP spatial site selection algorithm can be used to efficiently estimate soil textural properties. In our case, if we can afford to have 38 samples, we can allocate 20 sampling locations spread all over the watershed and six locations each on spots with low medium and high ECₐ values to generate experimental semivariogram values at small separation distance.

The study has shown that multivariate kriging methods that took ECₐ data into consideration when estimating clay percentage perform better than methods such as OK that use only univariate data. Moreover, the integration of ECa as well as spatial location
data in the RK method has produced more accurate clay percentage prediction maps as can be attested by the improved estimation RMSE.

**CONCLUSIONS**

In this study, the use of electromagnetic induction mapping provided a rapid and non-destructive method of densely sampling the subsurface of a small (~38 ha) watershed to produce an exhaustive map of apparent electrical conductivity – a surrogate property that is well correlated with clay percentage (r=0.84). Due to the relative time-invariant characteristics of textural properties, we were able to correlate clay samples collected over three seasons to EC$_a$ data of one mapping event. We then used three kriging methods that integrated various levels of information (clay percentage, EC$_a$, and spatial location) to produce clay percentage prediction maps. The multivariate estimation methods, incorporating the better sampled surrogate EC$_a$, were able to predict more accurately than univariate ordinary kriging. Leave-one-out cross-validation showed that cokriging and regression kriging by integrating EC$_a$ data were able to improve the RMSE by 7% and 28%, respectively, relative to ordinary kriging that used only clay percentage data. An uncertainty map for the clay percentage prediction map was produced by taking the standard deviation of 100 equally probable realizations of RK clay percentage maps, the SD for about 95% of the RK prediction is only between 1 and 3%. Electromagnetic induction mapping can provide an extra layer of information that can improve the prediction of spatially-detailed soil texture maps for studying soil hydraulic properties.
REFERENCES


Fig. 5-1. Air photo of the Reynolds Mountain East (RME) sub-watershed boundary (red line), contour lines in meters (black), perennial stream (white) and soil series delineation (dotted yellow line) from NRCS Soil Survey with soil unit 1 being classified as the Parkay-Dehana association and soil unit 2 as the Parkay-Bergar complex.
Fig. 5-2. A) Kriged map for 2007 ECₐ measurements with an overlay of soil sampling points and B) standard deviation (SD) map produced from 100 aggregated realizations of Sequential Gaussian simulation (SGSIM) maps.
Fig. 5-3. A) The relationship between apparent electrical conductivity ($EC_a$) and clay percentage  
B) Scatter diagram of the relationship between observed and modeled clay percentage from equation 10, and the 1:1 line.
Fig. 5-4. Experimental (dots) and modeled (solid line) normal score semivariograms for A) clay percentage data, B) EC\textsubscript{a} data, C) cross semivariogram between clay percentage and EC\textsubscript{a}, and D) residual semivariogram of clay percentage from equation 10.
Fig. 5-5. Clay percentage prediction maps produced using A) ordinary kriging (OK), B) Cokriging (CK) and C) regression kriging (RK).
Fig. 5-6. Box plots showing the distribution of estimated clay percentage for the three kriging methods.
Fig. 5-7 Components of regression kriging (RK): A) clay percentage map produced from a multiple linear regression (MLR) model (Equation 10); B) map of the residuals of the clay percentage MLR model; C) RK clay percentage map produced by adding together map (A) and map (B); and D) standard deviation map for the RK clay percentage map.
Fig. 5-8. Sequential Gaussian simulation (SGSIM) of clay percentage residuals. A and B are two equally probable stochastic realizations of the clay percentage residuals.
Fig 5-9. a) The relationship between observed and estimated clay percentage for the three kriging methods using leave one out cross validation - the sample correlation coefficient between observed and estimated clay percentage for RK was 0.86, while it was 0.73 and 0.74 for OK and CK, respectively. b) The ratio of estimation error to the observed value as related to the observed clay percentage value for the three kriging methods.
Fig 5-10. Root mean square error for the three prediction methods (relative to ordinary kriging) as a function of the number of samples. The actual RMSE values for OK are presented on top in brackets.
CHAPTER 6
SUMMARY AND CONCLUSIONS

Geophysical methods such as electromagnetic induction (EMI) provide the possibility of obtaining high resolution apparent electrical conductivity (ECₐ) images across a landscape that can be correlated with soil spatial properties and can identify subtle changes in subsurface soil patterns. Several factors influence ECₐ measurements including soil salinity, water content, porosity, structure, temperature, clay content, mineralogy, cation exchange capacity (CEC), and bulk density. An electromagnetic induction instrument transmits a low frequency (lower KHz) electromagnetic field into the subsurface, whereby it induces current loops in proportion to the subsurface ECₐ. The current loops in turn induce secondary magnetic field loops which are picked up by the receiver of the instrument. This non-invasive technique is appropriate for field scale measurement due to its rapid response, ease of integration into mobile vehicular measuring platforms, and nondestructive and non-contact requirements.

The reliability of data collected with EMI instruments depends on the thermal stability of the instrument, while the ECₐ measurement averaging over the soil profile depends on the configuration of the instrument coils. A study was conducted to compare the ECₐ – depth relationship between the DUALEM-1S and Geonics EM38-DD devices and to determine the effect of variable temperature environments on instrumental response. The measured response of the instruments with depth could be better fitted to inverse models using the DUALEM-1S data as compared to the EM38-DD output. This was much more apparent for measurements in the low conductivity soil where instrument
calibration difficulty made data inversion unfeasible using the EM38-DD. Results from the simple three-layer model over a conductive earth indicate that advanced optimization techniques or inversion models are required to obtain improved predictions of conducting layer structure. Our measurements over a range of temperatures indicate that at low EC\(_a\) both the EM38-DD and DUALEM-1S are more susceptible to instrument drift; this reduces considerably at higher values of EC\(_a\). The V-H\(_{DLM}\) configuration of the DUALEM-1S appears to correspond well with predicted values at low EC\(_a\). The EM38-DD readings appeared to be more temperature sensitive at lower EC\(_a\) exhibiting the opposite trend to the expected increase in EC\(_a\) as temperature increased. An improved method of temperature correcting for the instruments is required and should improve the accuracy of the instruments. For those using these instruments for an extended period to map soil properties (e.g. soil texture) where EC\(_a\) values tend to be low, we recommend that the mapping is performed on a cooler day or that the instruments are protected from direct sunlight. In this instrument comparison the EM38-DD’s real-time display and internal powering proved to be its advantages while the lower priced DUALEM-1S is less temperature sensitive, does not require manual instrument calibration and can store data internally.

Geo-referenced EC\(_a\) measurements were then taken using the DUALEM-1S on six different days at varying soil water content on a 50 × 50 m agricultural field at the Utah State University (USU) Greenville Farm to investigate the use of EMI mapping in challengingly low EC\(_a\) soils in order to capture the time invariant soil properties such as soil texture. We developed and tested a multi-mapping methodology and analysis
procedure of non-saline soils to differentiate static soil characteristics such as texture from the dynamic property of soil water content. This allowed us to identify locations offering consistent behavior over a range of soil water content. Once the composite maps are produced, decisions can be made as to whether soil calibration is required or if the obtained information is sufficient for the purposes of identifying management zones.

Ordinary block kriging was used to predict $EC_a$ at unsampled areas to produce 1-m resolution maps. Temporal stability analysis was used to divide the field into three regions exhibiting distinct $EC_a$ patterns. Subsequent ground-truthing confirmed that the lowest conductivity region was associated with a high energy channel that deposited coarser materials in the formation of the soil. There was also a statistically significant difference ($p=0.023$) in the average fine particle percentage between the other two delineated regions. If physically or economically limited to one mapping event, the strongest texturally induced $EC_a$ differences in the Millville soil were observed below field capacity. The $EC_a$ survey at $\theta_v = 0.16$ had the highest coefficient of variation and exhibited a multimodal histogram with distinct peaks associated with each delineated region.

The repeated EMI mapping of low $EC_a$ soils at varying water content reveals the textural patterns of the subsurface. The fact that the range of $EC_a$ at the USU Greenville Farm was only about 10 mS m$^{-1}$ makes the adaptation of this methodology into areas with a larger $EC_a$ range more informative. Thus repeated EMI mapping can be useful in soil surveys to delineate areas of soil heterogeneity as well as to better define transition zones between soil units. The methodology should be considered a tremendous benefit in the
arsenal of tools used by the soil surveyor, especially for site-specific soil maps. The methodology could be useful in precision agriculture in demarcating productivity and management zones for improved utilization of resources and better yield without the need for extensive calibration. The methodology could also be used to improve sampling schemes, especially in pristine environments, by providing an extra layer of information on soil variability and determining locations where maximum or minimum change occurs. This information could be very helpful for the potential placement of monitoring equipment, sensors and observation nodes for monitoring soil hydrological processes in situ.

In addition, EMI mapping was used to image the subsurface of the 38 ha Reynolds Mountain East (RME) watershed located near Boise, Idaho. The purpose was to provide a quantitative assessment of the landscape and its subsurface connectivity and storage capacity. We presented an imaging approach using kriging to interpolate, and sequential Gaussian simulation to estimate the uncertainty in the EMI maps. The observed patterns were informative in a qualitative sense, but we went on to show how the EMI data can be used to provide a more detailed estimate of watershed soil properties than simply using traditional soil survey maps. The traditional low-level soil survey for the area provided a watershed average soil water holding capacity (SWHC) of 0.13 m$^3$ m$^{-3}$, a reasonable estimate but one that lacked revelation of the soil spatial patterns. The geophysical image captured the soil patterns and their connectivity and provided an area average SWHC of 0.11 m$^3$ m$^{-3}$, with a range varying between 0.07 and 0.21 m$^3$ m$^{-3}$. 
Another interesting aspect of this research included differencing of EMI maps measured during wet and dry periods, which was useful in identifying hydrologically active locations. An exploratory univariate data analysis was performed on the georeferenced EC$_a$ data that was collected for the two mapping dates. The data for the 2006 and 2007 surveys were comparable and had means that were very close; 21.7 and 20.7, respectively. The 2006 EC$_a$ survey exhibited higher upper quartile values corresponding to the deep high water holding capacity soils; while the 2007 survey had a higher range of lower quartile values due to drier soils. We subtracted the dry (2007) EC$_a$ map from the wet (2006) map and examined the change in EC$_a$ as a proxy for observing changes in water storage. We interpreted the areas with a large positive change to be associated with deep soils that had higher clay percentage and higher water holding capacity, while those with little or no change were viewed as shallow, often more stony soils. Finally, those locations with a high negative change, we interpreted as soils with the possibility of some ion accumulation. The areas exhibiting the largest changes were located on the eastern side of the watershed, where more vegetative growth was observed and may indicate water use by the trees and shrubs.

In addition, combining the EMI map with DEM derived flow paths gave insight into the spatial textural structure in relation to distance from a flowpath. We looked at how the average EC$_a$ of a 5m buffer area varied as the buffer moved away from the channel network. We observed a constant decline in the average EC$_a$ up to 50m away from the channel network and subsequent leveling of the average EC$_a$ for the next 100 m. This is in broad agreement with the concept of soil catena, from which we would expect
the fine textured materials to accumulate in downslope positions in the landscape. Given the strong correlation between clay percentage and the EMI measurement, this is strong qualitative evidence that the EMI mapping is picking up the soil textural patterns of the watershed. The data and its interpretation indicates the usefulness of using geophysics to map small watersheds and opens a new opportunity to combine measurement and modeling approaches to better understand watershed scale hydrological processes.

We continued our research at the RME Watershed by making use of the EMI maps as a surrogate variable in order to predict clay percentage at unsampled locations using kriging methods that integrate different levels of information such as clay percentage, apparent electrical conductivity (EC$_a$), and spatial location. The electrical conductivity from the 2007 survey ranged from 0.3 to 128 mS m$^{-1}$, the average was 20.7 mS m$^{-1}$ with a median of 13.3 mS m$^{-1}$ and a standard deviation (SD) of 18.4. The clay percentage from the textural analysis of the soil samples ranged from 2.5 to 46.7, with a mean of 20.7 and SD of 11. The fact that our clay samples were collected over three mapping seasons brought its own complications. We had observed that the EC$_a$ values of the same sampling locations were changing seasonally due to differences brought about by factors such as water content. The effect of water content on EC$_a$ values from a dry to a wet season was quite significant with some areas showing a change as high as 30 mS m$^{-1}$. These differences ruled out the use of combinations of EC$_a$ values from the three mapping seasons. Instead we decided to use EC$_a$ data from only one mapping season in order to remove the seasonal effects of soil moisture. The relative time-invariant
character of textural properties made it possible to use a single season’s EC$$\text{a}$$ data to compare with clay percentage collected over three seasons.

Our results show that the multivariate estimation methods incorporating the information in the more thoroughly sampled EC$$\text{a}$$ data exhibit a lower RMSE of estimation. Leave-one-out cross-validation showed that cokriging (CK) and regression kriging (RK) by integrating EC$$\text{a}$$ data were able to improve the RMSE by 7% and 28%, respectively, relative to ordinary kriging (OK) that used only clay percentage data. We also looked at the effect of the number of samples used for estimation on the RMSE of the three kriging methods by comparing different seasonal combinations of sampling. The multivariate kriging methods that incorporated EC$$\text{a}$$ performed better than OK at different sample combinations; with CK showing a relative improvement of 5 to 10% over OK, and a higher relative improvement ranging from 25 to 40% for RK, due to the inclusion of spatial location information.

If limited to fewer samples due to time constraints or limited funds, it might be advisable to utilize RK over the other methods described since RK can include more information in the prediction process. The limiting factor being enough samples to generate a semivariogram, RK combined with a surface response spatial site selection algorithm can be used to efficiently estimate soil textural properties. In our case, if we can afford to have 38 samples, we can allocate to have 20 sampling locations spread all over the watershed and 6 locations each on spots with low medium and high EC$$\text{a}$$ values to generate experimental semivariogram values at small separation distances.
Electromagnetic induction mapping can provide an extra layer of information that can improve the quality and resolution of spatially-detailed soil texture maps that are used in hydrological, environmental, and agricultural research. This study has shown that multivariate kriging methods that took ECₐ data into consideration when estimating clay percentage perform better than methods such as OK that use only univariate data. Moreover, the integration of ECₐ as well as spatial location data in the RK method has produced more accurate clay percentage prediction maps as can be attested by the reduced estimation RMSE.

Such spatially-detailed soil textural maps can be useful in studying the discrepancy between measured hydrographs and model predictions, where average values used for soil moisture and soil hydraulic parameters can lead to large deviations. Such maps will be useful in understanding the effect of the spatial correlation of infiltration patterns in runoff pathways connectivity as well as modeled runoff uncertainty.
APPENDICES
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APPENDIX B

Eco-Geophysical Imaging of Watershed-Scale Soil Patterns Links with Plant Community Spatial Patterns

ABSTRACT

The extent to which soil moisture, and nutrient availability control the structure, function, and diversity of plant communities has aroused considerable interest in the past decade, and remains topical in light of global change. Numerous plant communities are controlled either by water or soil nutrient availability, and yet spatial patterns of soil properties affecting resource pools, such as texture, are often poorly delineated at the landscape level. Traditional soil survey methods, developed for land evaluation, remain largely qualitative based on the subjective analysis of the soil surveyor, often using vegetation patterns to demarcate soil boundaries. To date, no independent method of determining the properties of soil root-zone spatial-patterns has been developed for use at the landscape scale, resulting in a knowledge gap between observed above ground vegetation patterns and the distribution of below ground soil properties. The objective of this work was to determine if a quantitative link could be observed between bulk soil electrical conductivity, used as an indicator of soil texture, and the plant community spatial pattern using geophysics. By comparing the geophysical signal with plant community patterns, we have discovered distinct vegetation niches corresponding to

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distinct zones of bulk soil electrical conductivity. A hierarchical ranking of the mean bulk soil electrical conductivity for each plant community type follows a power-law structure.

**INTRODUCTION**

A critical challenge facing the scientific community is the need to determine the potential impact of global climate and land-use change on the structure, function and diversity of ecosystems (Wardle et al., 2004). This challenge requires that we develop an understanding of the extent to which the availability of soil resources, nutrients and soil water content, control ecosystems (Rodriguez-Iturbe and Porporato 2004, Eagleson 2002); and conversely how ecosystems control the availability of soil nutrient and water resources. The nature of these relationships will depend on the scale of observation. Often it is the smaller scales at which we want to understand processes, but then upscale these into models describing regional patterns (Huston, 1999). However, complex systems theory tells us that the behavior of the individual is not necessarily the behavior of the group, and ecological patterns are not simply additive. Therefore, to study soil-plant community patterns we have to, at least, look at the behavior within watershed boundaries. The watershed serves as a natural delimiter for water inputs and throughflows, and it may help us to better understand 'emergent' or 'collective' patterns on the landscape.

Soil properties can be measured by destructive sampling at a point, but to measure at multiple points is time consuming and labor intensive. Therefore, at the landscape scale, soil types are classified based on a soil surveyor's knowledge of soil forming
processes and a subjective interpretation of the landscape. Vegetation patterns are often one of the criteria used by soil surveyors to delineate soil boundaries. Thus a somewhat circular argument develops, where by relationships between vegetation and soils are inferred from mapped soil distributions, but the vegetation was already used to define the soil boundaries. If we wish to really explore soil-plant spatial relationships soil maps developed independently from vegetation are required.

Ecohydrological processes in watersheds are tightly coupled with soil properties. For example, soil texture and soil depth control the available soil water, which in turn controls leaf area index (LAI), which increases under abundant soil moisture availability. The larger the LAI the more incoming rainfall (or precipitation) is intercepted by the canopy, and potentially evaporated before reaching the soil surface, thus reducing the amount of water infiltrating into the soil. This soil controlled feedback mechanism therefore exerts a strong control on plant community structure, especially in semi-arid environments. Watershed modeling approaches have demonstrated the sensitivity to soil type of both evapotranspiration (ET), and the plant canopy net photosynthesis, and resulting biomass production (Band et al., 1993). Though the importance of these processes is known, van Dijk (2004) has argued that, 'to date, no consistent physical theory has been developed to describe the relationships between topography, ecosystem maintenance and modification of soil structure, and the alteration of soil hydraulic properties all of which contribute to the expression of plant community structure, and are fundamental to understanding the long-term impacts of climate and land-use change. A distinct knowledge gap therefore exists that relates soil spatial properties, watershed
hydrological processes and response, and plant community spatial patterns. We contend that this knowledge gap occurs in part due to the limitation of quantitative, root-zone, spatially-exhaustive soil property data. Observation made at pertinent scales is fundamental to developing and testing ecosystem models and is a driving force behind the National Ecological Observation Network (NEON (Kaiser, 2003)) and the Consortium of Universities for the Advancement of Hydrological Sciences Inc. (CUAHSI (Torgersen, 2006)) observatory initiatives in the US. Given the scientific goals of these initiatives, there is a great interest in tools or methodologies that can contribute to our understanding of emergent patterns or behavior at the watershed or landscape level.

In this paper we address this issue of insufficient, independent, quantitative, landscape-scale soil information by applying geophysical imaging to a research watershed in Idaho that exhibits strong vegetation patterns. With the specific objectives of 1) measuring the spatial geophysical properties of soils as a surrogate for mineral soil texture, and 2) relating the geophysical response to the vegetation community spatial patterns. The traditional soil survey does not provide sufficient information to draw any conclusions about the relationship between the observed ground cover types and the soil properties. However, by obtaining a geoelectrical image of the soils using electromagnetic induction (EMI) we have discovered distinct relationships between geoelectrical signatures and ground cover type. This results in a novel advance: a geoelectrical map that can be used to infer soil textural boundaries, and identify a
quantitative link between the geophysical signature and the ground cover type that can be used to identify and explore community niche structure at the landscape scale.

METHODS

Study Area

The Reynolds Mountain East Experimental Watershed, near Boise, Idaho, USA is an example of a semi-arid, rangeland ecosystem; with several montagne characteristics including steep slopes in places, some shallow weakly developed soils, and bedrock exposure. An air photo of the watershed is presented in Fig. 1a. It has a range of both nutrient and water limited soils (Grant et al., 2004). Overlaid on the map (Fig. 1a) is the NRCS soil survey series boundaries. The soil survey identifies two soil mapping units, the area with yellow hatching (121), Parkay-Bregar complex and the area outside this (120) as the Parkay-Dehana association. Soil 120, is classified as a gravelly loam, and 121 as a gravelly silt loam. The estimated clay % is very similar for both soils, 19.2 % (120) and 22.3 % (121); the amount of silt separates these soils 38.4 % (120) and 47.7 % (121) for classification purposes. The term gravelly indicates stone content of greater than 15% for particles more than 2mm in diameter. Notice how the soil boundary closely follows the change in vegetation from woody-covered to grass and shrub dominated zones.

The mean annual precipitation for the watershed is 994 mm with 76% in the form of snow between November and April; July and August get minimal precipitation. Snow drifts form in locations A, B and C (Fig. 1a) and cause unevenly distributed water inputs
into the watershed (Marks et al., 2002). Nine major ground cover types were identified and mapped using air photographs and GPS mapping on the ground (Fig. 1b), to give 10×10 m pixels, and were considered to be a strong reflection of the soil properties and hydrological flow-paths in the watershed. Of the nine ground cover types mapped, eight were vegetation communities and one was bare stony ground where rock outcrops occurred (stony Fig 1a). The eight plant communities were identified as, grasses and forbs, including i) (G1) sparse (space in between individual plants) and ii) (G2) dense communities (no space in between individual plants); shrub communities dominated by iii) (SB) snowbrush, *Ceanothus velutinus* and iv) (S1) sparse and v) (S2) dense mountain big sagebrush, *Artemisia tridentata vaseyana*; and woodland, including vi) fir, mixed species dominated by subalpine fir, *Abies lasiocarpa* and douglas fir, *Pseudotsuga menziesii*; and communities of vii) willow, *Salix* sp., and viii) quaking aspen, *Populus tremuloides*.

**Geophysical soil mapping**

Unlike a traditional soil survey, that might sample 10-15 soil profiles per day, our use of an EMI system allowed us to obtain ~10,000 measurements of bulk soil electrical conductivity (ECa) per day across the 41-ha semi-arid watershed. EMI survey has been used for soil salinity assessment in land reclamation and agriculture where the ECa response is dominated by soil salinity (Lesch et al, 1992; 2005). The application to hydrology and ecology has been limited to date (Slater and Reeve, 2002), primarily because of limitations for measurements under tree canopies which modern GPS technology is now overcomming.
ECa depends primarily on soil texture (% clay), volumetric water content (VWC), solute concentration and temperature (Friedman, 2005). At constant temperature, increases in % clay, water content, or solute concentration will increase ECa. Hence in non-saline soils a higher ECa reflects greater % clay or VWC. Although this is not a unique relationship we demonstrate that ECa in non-saline soils can serve as a quantitative spatial delineator of texture, and the associated difference in VWC due to textural change. Given that the cation exchange capacity (CEC) of the clay is a major control over the retention and availability of nutrients, ECa, when related to soil texture, may provide a surrogate estimator of 'soil nutrient status' that may correspond to plant communities and ecosystem transitions or ecotones.

We used a DUALEM 1S electromagnetic induction sensor carried at a height of 0.4m above the ground, connected to a field computer and GPS to determine the bulk soil electrical conductivity (ECa). Measurements were recorded using the vertical coil orientation with an estimated depth of penetration of ~0.6 m based on the instruments sensitivity weighting (Abdu et al., 2007; Callegary et al., 2007). The measurements were made July 17th and 18th 2006 by traversing the watershed whilst recording the data from the EMI instrument (Fig. 2). The dates chosen were consistent with dry weather one month after the snowmelt had completed. Sampling in July was considered optimal as gravitational water had drained from the soils but the plant transpiration had not significantly depleted the root-zone soil moisture. The effects of temperature on ECa were considered negligible as repeated measurement of ECa at different times in the day gave the same response.
The field site had a variety of metallic access tubes and instrumentation buried in the ground. An effort was made to avoid obvious metallic structures or fences. The data were checked for consistency, and outlier values observed at locations consistent with metallic objects, were removed. Outliers associated with metallic objects were identified by a distinct drop in ECa, usually negative, followed by values often in excess of 200 mS/m. The raw ECa data were asymmetric, skewed towards the low ECa values.

Block-kriging, with 10×10 m blocks, was used to obtain a map of the bulk soil electrical conductivity (Nielsen and Wendroth 2003). The data were transformed using a normal score transform (Deutsch and Journel, 1992) to give a Gaussian distribution with a mean of zero and variance of one. The normal score transform procedure in the program SGems (Remy, 2004) breaks the ties between data with the same value, no extrapolation of the tails was used. Vesper (Walter et al., 2001) was used to obtain a local-semivariogram of the data which was fitted with a spherical model with a sill of 1.0. Block-kriging was performed on a 10×10 m grid using the local variogram, over the entire watershed as defined by the boundary in Fig. 2. Finally the kriged normal score data was back transformed to give the watershed map of bulk soil electrical conductivity.

Basic protocols for soil sampling were adapted from Corwin and Lesch (2005). A statistical soil sampling plan was generated from the response surface created using two sets of EMI data, 20 samples were located based on a survey of the entire watershed and 20 samples were located at the southern end of the watershed where strong vegetation patterns occur (Fig 2). For this procedure, the methods described in (Lesch, 2005) were used. These methods ensured that the samples were evenly spaced throughout the
mapped zones and at the same time covered a representative range of ECa. The aim of the sampling was to test the correlation between EMI signal response and measured soil properties, rather than map soil properties based on soil sampling which would require many more samples. Forty soil samples to 0.3 m depth were removed from sampling points across the watershed. Sub-samples were oven dried at 105°C to determine volumetric water content. Sub-samples were used to determine the clay % using standard pipette analysis (Gee and Bauder, 1986) and for the saturation paste extract soil solution electrical conductivity. The 10×10 m grid used in the kriging was overlaid as a geo-rectified image onto an air-photo of the watershed. The vegetation community type in each of the 4120 grid cells was determined from the overlay, by checking photographs, and by visual observation in the watershed with GPS.

RESULTS AND DISCUSSION

Fifteen thousand, non-invasive, ECa measurements were obtained over two days by traversing the watershed on foot with an EMI system. Interpolation and spatial averaging of the measurements, using block-kriging, produced an ECa map of the watershed with a 10×10 m pixel size (Fig. 3) and a data range of values from a minimum of 0.1 to a maximum of 117 mS/m. The soils on the eastern side of the watershed gave a much higher ECa response than in other locations. Calibration of the signal response with ~40 laboratory analyzed soil samples found ECa to be positively correlated with soil clay % ($r^2 = 0.73$) and VWC ($r^2 = 0.73$) sampled in the top 0.3m of soil (Fig. 4a); the ECa was more sensitive to clay % than to VWC. There was a weak correlation between ECa and
the electrical conductivity of the soil solution extract (ECe) \( (r^2 = 0.45) \), likely due to the dominance of the clay % on the signal and ECe values typically lower than 70 mS m\(^{-1}\). Therefore, we interpret variation in ECa, in this watershed, to be controlled by changes in clay and the associated soil VWC, two parameters which are themselves positively correlated due to the soil water retention properties of clays. Visual observation suggests that the EMI reading is not a good surrogate for water content, only where it is strongly correlated with texture. For example, saturated organic rich soil along the riparian zone had a low ECa but very high water content. Textural analysis of the soil samples indicated a broad range of fine earth soil textures (Fig. 4b), in strong contrast to the average soil texture values assigned by the soil survey and shown as blue dots in Fig 4b.

Comparison of the watershed ECa map (Fig 3) and the soil boundaries interpreted by the survey (Fig 3, yellow line) demonstrate substantial inconsistency between the location of soil boundaries identified by the two contrasting approaches. The subjective soil survey boundary is observed to follow the boundary between the woodland dominated zone and the shrub and grass dominated zone. One would conclude from this that the trees tend to grow on soil 121 with more fine particles, and that the grasses and shrubs are constrained to the coarser textured soil 120. The ECa map, considered to reflect changes in soil texture across the watershed, indicates boundaries consistent with topographical features observed on the ground, e.g. the accumulation of fines in low lying depositional areas. The EMI results demarcate soil boundaries in the eastern sub-catchment (Fig. 3). In this area higher levels of clay and soil water, as determined from the soil samples, combine to give higher ECa responses. What is noteworthy about this
map is that the EMI signal identifies what appear to be locations of higher ECa, consistent with landscape position and flow-paths interpreted from air photographs and observations on the ground. Colluvial transport of clays through the soils, and the depositional processes, lead to locations with increased clay and higher water content, fostering lush vegetation growth; these areas have higher ECa values, and appear red and yellow in Fig. 3.

A variety of control mechanisms are known to influence the vegetation community structure in these rangeland ecosystems including, fire with a historical fire cycle of 20-25 years, although the last significant wildfire in the watershed occurred in the mid 1930's (Hardegree, et al., 2007); grazing (Johnson et al., 1980) and also exposure, which influences the location of drifting snow (Marks et al., 2001). The data gathered during this research allows us to determine the role that soils exert, particularly texture and the associated soil moisture. A factor that remains unexplored is soil depth, this certainly acts as a control in certain parts of the watershed, especially in areas with the stony outcrops (Fig 1 b).

A simple overlay of the aspen and dense meadow grass (G2) community boundaries (dominated by Idaho fescue, *Festuca idahoensis* and some sandberg bluegrass, *Poaceae secunda* J. Presl) on the ECa map (Fig. 3), indicate remarkable correspondence between the spatial boundaries of the high ECa soils and the two plant communities and their ecotone. The observed patterns offer firm evidence that the aspen and dense meadow grass community structure is strongly associated with soil properties, that most likely affect nutrient and water resource pool availability.
The vegetation map, overlayed on the ECa map, allowed the assignment of an ECa value to each 10×10m pixel. This is plotted as a box-whisker plot (Fig. 5) in terms of the ECa response for the eight vegetation communities. It reveals the emergence of a distinct hierarchical structure with regard to the plant communities and the soil type. The outliers (Fig 5), red markers, are in general associated with plant community transition zones. For example, the outliers in the fir community correspond to the fir trees associated with, and intermixed with, the aspen communities (Fig 1b). When the distributions are ranked from lowest to highest, as in Fig. 5, an almost power law dependence \(0.908x^{1.8285} (r^2=0.98)\) of plant community on true mean soil ECa emerges. The observed power-law dependence indicates a very strong coupling between the observed above ground plant community pattern and below ground soil type.

Of the tree communities the fir and willow dominate the low ECa soils, and are also close to the surface water resources. The willows occupy the stream riparian zone, transitioning to fir above the location where the surface water emerges in the watershed. The mature fir stand is situated on coarse textured soils, indicated by low ECa values; these soils are also high in organic detritus. The coarse textured soils favor water infiltration deep into the subsurface. The trees rely on capturing water derived from snow melt and are situated in locations down-slope from the areas where the snow drifts form (Fig.1a).

The wide distribution of ECa values (Fig 5) associated with the S2, G2 and aspen communities indicates that texture is only one influencing factor on the vegetation spatial patterns; other factors affecting vegetation spatial patterns may include fire and grazing.
Fire may play a long term role while grazing is not considered to have a strong negative impact on biomass in this watershed. In the short-term soil moisture and soil moisture storage are considered to most likely control these vegetation patterns, and the soil moisture at least is strongly correlated with the soil texture. Soil moisture is also strongly linked to the relief due to the way in which snow is blown around the watershed creating major drifts in specific locations (Fig 1a). Access to soil water is likely to be a control on the distribution of these plant communities (S2, aspen and G2), and the community boundaries are consistent with subsurface textural distribution and flow-path locations that determine soil water content distribution. As both the texture and water distributions are dependent on relief, strong links between plant community patterns and position in the landscape should be expected. Water content is also an important moderator of soil biogeochemical cycling and in many cases controls microbial activity in the soil, which in turn controls processes such as nitrogen mineralization and carbon turnover affecting the supply of nutrients to plants (Schjonning et al., 2003). The evidence presented by the soil ECa data indicates that knowledge of soil texture and by inference the soil water content, serve as useful indicators of plant community spatial patterns. These observations add information layers about abiotic factors that can be used to better understand the spatial patterns and the processes that drive spatial pattern formation and maintenance.

In stark contrast to the other plant communities the snowbrush (SB) has a very distinct niche, in low electrical conductivity soils with very few outliers. It is confined to locations where the ECa is less than 2.9 mS m\(^{-1}\) and an average of 1.2 mS m\(^{-1}\). This ECa
is exceptionally low, indicating soil with no clay and therefore limited capacity to store nutrients. As snowbrush is a nitrogen fixer it is not limited to soils with conditions conducive to nitrification, and can exploit nutrient depleted soils. As soon as the ECa rises the snowbrush gives way to the sparse and stunted mountain big sage community (S1) which also has a low average ECa (2.7 mS/m). In contrast the dense mountain big sage community (S2), which comprises perhaps 40% snowberry *Symphoricarpos oreophilus*, occurs on the soils with a mean ECa of 21.4 mS m$^{-1}$. Although S2 spans a range of soil ECa from 0 to ~70 mS m$^{-1}$, the distribution is skewed toward low ECa values (median, 14.9 mS m$^{-1}$). Noticeably, the distribution of S2 tends to be around the edges of the G2 and aspen communities. Observation on the ground indicated that the location of the transition between G2 and S2 corresponds in many instances with a sharp transition from loam to clay loam soils as observed from soil samples.

Distribution statistics are presented in Table 1, along with the area that the vegetation communities occupy. The communities were divided according to their skew, those with a skew greater than 1 were considered log-normal and the mean, std dev, and coefficient of variation, CV, were determined for the lognormal distribution. Those with a skew <1 were treated as normal. The ecological significance of the CV for the ECa distribution for a given plant community is unclear. However, we consider that plants endeavor to occupy their potential niche whilst competing for resources. In this work we consider the ECa to reflect soil type/clay%, and assume that given a soil texture gradient and no external competition a plant community would follow closely to a normal or slightly skewed normal distribution. This assumes an optimal soil texture to maximize the
capture of resources, e.g. soil moisture and nutrients. We consider that highly skewed 
ECa distributions for a vegetation community may indicate communities that are 
removed from their optimal conditions / niche. We also speculate that the high CV's 
associated with these distributions indicate far from ideal soil and resource supply 
conditions. We interpret normal distributions with low CV values as indicating 
communities closer to optimal conditions and niche fulfillment.

Based on this interpretation we consider that the ranked CV, which follows a 
power law decline from the highest (G1) to the lowest (SB) CV, (CV = 3.9271x^{-1.0165} 
(r^2=0.96)) indicates increasing niche stability toward the lowest values. Due to climate 
change, it is expected in the future that increases in rainfall, and a reduction in snow 
water equivalent will occur (Barnett et al., 2005). Consequently we might expect to see 
different patterns of 'change' in these ecosystems. The communities with lognormal 
distributions and high CV's might be expected to be more sensitive to environmental 
change as they are already further from optimal conditions. A decrease in soil moisture 
should impact the more water demanding species on droughty soils. Comparison of air 
photos of the watershed from the 1960's with recent images does indicate an observable 
reduction in the density of the fir stands during this period, most likely due to changes in 
the hydrological conditions, and is the subject of ongoing research.

At regional and continental scales indicators such as mean average precipitation 
(MAP) (Sankaran et al., 2005) can be useful for understanding broad patterns of plant 
community structure, especially where changes in topography (relief, slope, and 
elevation) and soil properties are not significant. However, we contend that at watershed
scales especially as topography becomes more significant, associated soil patterns will become more variable across the landscape and in turn influence vegetation patterns. In soils on areas with low topography, fine particles tend to be transported vertically downwards through the soil profile, resulting in increasing fine particle accumulation with depth; this process tends to result in relatively uniform soil spatial patterns across the landscape. In contrast, areas exhibiting marked topographic change generate lateral flows, so that lateral colluvial transport of fine particles through soils occurs. Hillslope colluvial movement and erosion results in the removal of fines from upslope positions and their deposition in low-lying landscape positions. Therefore, undulating landscapes tend to show more heterogeneous soil patterns than soils on plains given uniform parent materials. As a result, we would expect that soil patterns would play an increasingly important role in determining local vegetation patterns as topography becomes more heterogeneous and therefore controls resource gradients such as water and nutrients. The geophysical approach outlined in this research provides a quantitative framework within which these questions concerning abiotic factors controlling vegetation patterns can be more fully addressed. It offers alternative quantitative spatial soil pattern data, rather than the more subjective, qualitative, traditional soil survey (Soil Survey Staff, 1999).

Review of the literature indicates that there has been a growth in the number of models aimed at improving rangeland management in semi-arid environments, whilst fewer are aimed at understanding ecosystem dynamics, especially hydrological, in semi-arid systems (Tietjen and Jeltsch, 2007). One of the reasons for this maybe a lack of quantitative, spatial, soils information that can be used as input to check and constrain
these modeling approaches; the very issue this geophysical approach addresses. Geophysical imaging also has the potential to be implemented at larger scales using airborne surveys. In a world of increasing climate and land use change, and an estimated 2 billion ha of soils degraded to some extent (Lal, 2001), this rapid, non-invasive, geophysical method provides a way of illuminating mineral soil textural properties and water resources and patterns, given sufficient contrast, in natural ecosystems that can provide a quantitative link between above and below ground ecosystem patterns. In turn, we can apply this to better understand community dynamics, especially with regard to global change, in vulnerable ecosystems, in response to factors such as climate forcing, land-use change and increasing pressure on water resources.

CONCLUSIONS

Geophysical ECa watershed imaging provides a novel and valuable resource for interpreting ecosystem spatial patterns considered to be influenced by abiotic properties. It offers insight into the distribution and patterns of soil properties related to soil ECa. Based on the independent soil image we were able to compare soil and vegetation patterns and determine linkages between plant communities and soil properties. In this work we discovered strong coupling between the geophysical signal (soil properties) and vegetation community patterns that were not evident based on the traditional soil survey approach. Close correspondence between the observed plant community structure and the soil clay % and soil VWC was demonstrated. In future work we hope that this technique can be deployed to assist in the design of vegetation sampling and the interpretation of
vegetation community patterns that may depend on soils, especially where changes in soils and vegetation patterns are more subtle and difficult to interpret using traditional, qualitative soil-surveying. The information obtained provides a novel method by which niche communities related to soil properties might be identified and delineated. The interconnectedness between plant community patterns, soil VWC, and landscape makes a strong case for ecological studies that encompass more detailed soil information over entire watersheds; the watershed being the natural delimiter of soils and water resources.

This work encourages the exploration of geophysical imaging as a method of obtaining quantitative data on soil patterns at the landscape level that can be used to explore above ground plant community patterns. The link between above and below ground patterns is often controversial due to the sparsity of data. The methodology and analysis presented, utilizing ~15,000 ECa measurements proposes a new way to obtain quantitative spatial data, when the geophysical contrast is significant enough, to identify differences between below ground properties that can be compared with the observed plant community patterns above ground. As with all geophysical methods we acknowledge that this method will have its limitations and may prove unsuitable for instance in determining patterns in organic soils or highly weathered soils.

REFERENCES


Table B-1. Summary statistics for the ECa values associated with the eight vegetation communities, (stony – bare ground with rock outcrops had 6% ) sparse grass (G1), Fir, sparse big mountain sage (S1), Willow, dense big mountain sage (S2), Aspen, snowbrush (SB), and dense meadow grass (G2). Values in bold had skew values >1 prior to transform, and were log-transformed and the log mean, stdev and CV determined.

<table>
<thead>
<tr>
<th>% of area</th>
<th>G1</th>
<th>Fir</th>
<th>S1</th>
<th>Willow</th>
<th>S2</th>
<th>Aspen</th>
<th>SB</th>
<th>G2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>16</td>
<td>7</td>
<td>11</td>
<td>7</td>
<td>22</td>
<td>13</td>
<td>2</td>
<td>16</td>
</tr>
<tr>
<td>Std. dev.</td>
<td>60.6</td>
<td>15.2</td>
<td>2.9</td>
<td>12.9</td>
<td>16.6</td>
<td>18.0</td>
<td>0.5</td>
<td>19.8</td>
</tr>
<tr>
<td>Coeff. of var. (CV)</td>
<td>3.581</td>
<td>2.116</td>
<td>1.130</td>
<td>0.847</td>
<td>0.776</td>
<td>0.500</td>
<td>0.417</td>
<td>0.375</td>
</tr>
</tbody>
</table>
Fig. B-1. a) Air photograph of the watershed showing the watershed boundary (red line), the surface water (blue line). The two soil types (121) and (120) identified by the soil survey are separated by the yellow line, 121 with hatched lines. The black lines are the 20m contours, spot heights at the weir and highest point are shown, and the primary locations where snow drifts form (A, B and C). b) Vegetation community map rendered at 10×10 m pixel resolution, stony – bare ground with rock outcrops, sparse grass (G1), dense meadow grass (G2), snowbrush (SB), sparse big mountain sage (S1), dense big mountain sage (S2), trees as labeled.
Fig. B-2. The route taken to obtain the ~15,000 EMI measurements. The red circles indicate the sampling points for determining soil texture and VWC.
Fig. B-3. Apparent electrical conductivity (ECa) map with 10×10 m pixels, overlaid with the boundaries of the aspen community (red line) and dense meadow grass (black line) on the watershed map. The red areas correspond to more clay and water in the soils, the dark blue to areas with coarse textures.
Fig. B-4. a) Apparent electrical conductivity (ECa) as a function of clay % and volumetric water content % (VWC) in the top 30 cm of soil. Clay % is corrected for the percentage of stones in the total volume of soil. b) Soil texture triangle for samples taken from the watershed indicating a fine earth (< 2mm) textural range from sandy loam to clay. The blue dots indicate the soil textures assigned by the soil survey.
Fig. B-5. Box whisker plot of the soil bulk electrical conductivity (ECa) for each of the 8 vegetation communities. The boxes on the plot indicate the inter-quartile range, containing 50% of the data. The whiskers correspond to a maximum of 1.5 times the length of the inter-quartile range, the red markers are the outliers with the circles showing the more extreme. SB, snowbrush; S1, sparse mountain big sage; G1, sparse grasses and forbes; S2, dense mountain big sage; G2, dense meadow grasses and forbs. The red diamond is the average and the gap between the boxes marks the median, the black box is the interquartile range, the whiskers represent 1.5 times the interquartile range and the red markers are the outliers.
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