Repeated Electromagnetic Induction Surveys for Improved Soil Mapping in an Agricultural Landscape

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Soil apparent electrical conductivity (ECa) measured by electromagnetic induction (EMI) has been widely used to interpret soil spatial variability. We investigated the use of repeated EMI surveys, in combination with depth to bedrock and terrain attributes, to improve soil mapping in a 19.5-ha agricultural landscape. The first two surveys were done in 1997 and 2006, in which different meters (EM38, EM31, and Dualem-2), dipole orientations, and geometries were compared. The EM38 operated in vertical dipole orientation was then used in another six surveys in different seasons from 2008 to 2009. Results showed that the optimal use of EMI depends on the targeted soil properties, landscape characteristics, specific EMI meter and its setting, and the timing of the survey. The EM31 operated in vertical dipole orientation provided the deepest measurement depth (6 m) among the three meters used and showed the strongest relationship with depth to bedrock in the study area ($r^2 = 0.58$). Because the top 2 m of soil profiles exhibited distinct textural differences across the landscape, the EM31 operated in horizontal dipole orientation and Dualem-2 operated in horizontal co-planar geometry (both with 3-m measurement depth) showed the best correlation with silt content ($r^2 = 0.45–0.47$). The best EMI mapping of major soil distribution across this landscape requires optimal timing (wet period) and an appropriate meter and setting. No single EMI survey or the relative difference in ECa of repeated EMI surveys was sufficient to obtain the best possible soil map for the study area. Instead, a combination of repeated EMI surveys, depth to bedrock, and terrain attributes provided the best mapping of soils in this agricultural landscape and doubled the accuracy of map unit purity compared with the existing second-order soil map.

Abbreviations: API7, antecedent precipitation index during the previous seven days; DEM, digital elevation model; ECa, apparent soil electrical conductivity; EM31H, EM31 meter operated in horizontal dipole orientation; EM31V, EM31 meter operated in vertical dipole orientation; EM38V, EM38 meter operated in vertical dipole orientation; EMHCP, Dualem-2 meter operated in horizontal co-planar geometry; EMI, electromagnetic induction; EMPRP, Dualem-2 meter operated in perpendicular geometry.

Precision soil mapping is important not only for reliable research but also for site-specific management of soil, water, plants, and ecosystems. An accurate soil map is a foundation for understanding soil variability across the landscape and for modeling soil–landscape relationships. Traditional soil maps have been created from air photo interpretations based on collated information on landform, geology, vegetation, and land use, with limited field checking (Dijkerman, 1974; Soil Survey Division Staff, 1993). Unlike topography and vegetation, however, which can now be mapped with high resolution (e.g., using laser-induced differential absorption radar [LIDAR] for elevation and IKONOS satellite images for land use and land cover), detailed and accurate mapping of soils remains difficult. High-density ground-based observations, while highly valuable, are generally costly, time consuming, and destructive. Yet enormous local variability in soils and their various properties frequently demands high-density measurements. The lack of high-resolution maps of soil types and their properties has constrained the site-specific management of natural resources and the spatially distributed modeling of landscape processes (Sawyer, 1994; Rossel and McBratney, 1998; Lin et al., 2005a).
With the emergence of various geophysical tools, convenient and nondestructive means of quantifying subsurface variability have become more attractive; however, uncertainties in interpreting geophysical data for specific soil properties and subsurface features in the real landscape remain a challenge. Electromagnetic induction has been widely used to noninvasively measure ECa (e.g., Johnson et al., 2001; Sudduth et al., 2001), which can be correlated with soil properties such as clay content, mineralogy, soil moisture, depth to the water table, and salinity (e.g., Rhoades et al., 1976; McBride et al., 1990; Auerswald et al., 2001; Corwin and Lesch, 1976; Robinson et al., 2009; Zhu and Lin, 2009). Hence, soil ECa measurements have been widely used to map different soil properties including texture (Brus et al., 1992; James et al., 2003; Saey et al., 2009), soil type (Anderson-Cook et al., 2002; James et al., 2003), and soil moisture (Reedy and Scanlon, 2003; Sherlock and McDonnell, 2003; Zhu et al., 2010).

Because the factors affecting ECa are complex and interrelated, accurate interpretation remains a challenge. Mixed results have been reported in using EMI to interpret the spatial variation of soil properties. For example, Mueller et al. (2003) found that the effectiveness of ECa to predict soil clay content, Ca content, and the depth to an argillic horizon changed from field to field and from date to date. In their study, the coefficient of linear correlation between clay content and ECa varied from 0.26 to 0.86 at four different sites (possibly because of spatial variations of clay and moisture at different sites). One possible way to enhance the interpretation of EMI results is to conduct repeated EMI surveys in the same area at different times with either the same or different meters and coil configurations, and then to examine the differences and similarities among these surveys. Zhu et al. (2010) demonstrated the merits and limitations of using repeated EMI surveys to determine subsurface hydrologic dynamics. Other studies have also reported repeated EMI mappings to improve the interpretations of soil properties such as soil moisture, fertility, and salinity (Hanson and Kaita, 1997; Eigenberg et al., 2002; Sherlock and McDonnell, 2003). Similarities and differences among repeated EMI surveys and the question of how to incorporate observed ECa patterns into the detailed mapping of soils and their properties require further improvements.

Second-order soil maps (called SSURGO) are widely available in the United States and have cartographical scales of 1:12,000 to 1:63,360 with minimum delineation sizes of 0.6 to 16.2 ha (Soil Survey Division Staff, 1993). While highly valuable for general land use planning and many other applications, these second-order soil maps have encountered challenges for more precise applications in landscape studies, precision agriculture, catchment hydrology, and ecosystem services (e.g., Robert, 1993; Franzen et al., 2002; Lin et al., 2005a,b). In addition, traditional soil mapping methods generally have used qualitative models that produce broad schemes for discretizing and classifying the soil continuum and thus lack adequate quantitative data (Cook et al., 1996). For example, the impurity of the second-order soil map units has been challenged in many studies. Robert (1993) and Franzen et al. (2002) documented the inadequacy of second-order soil maps for optimal site-specific crop management and planning because the delineated map units contained substantial inclusions of other soil series and phases. Lin et al. (2006) also showed that the second-order map units were too coarse for the study of small-catchment hydrology and contained erroneous boundaries for the forest catchment they studied. To overcome these problems, ways for improving soil maps with a higher precision at a reasonable cost are needed.

Electromagnetic induction has been used to map soil distributions. Anderson-Cook et al. (2002) used an EM38 meter (Geonics Ltd., Mississauga, ON, Canada) and a crop yield map to delineate soil types for mid-Atlantic Coastal Plain soils. James et al. (2003) also used an EM38 meter to map the boundaries of soil types with distinct textural classes and field capacities. Greve and Greve (2004) used an EM38 meter to classify the transitional zones of different soil types. Brevik et al. (2006) reported that ECa values collected with an EM38 had the potential for differentiating adjacent soil series in Iowa. These earlier studies, however, have not adequately addressed temporal variations in soil ECa and their impacts on soil mapping.

The objective of this study was to investigate how repeated EMI surveys could be utilized to enhance the mapping of soils and the distribution of various soil properties (such as depth to bedrock, texture, and organic matter content) across a 19.5-ha agricultural landscape. Such work could pave the way for refining standard second-order soil maps through appropriately repeated EMI surveys together with terrain data.

**MATERIALS AND METHODS**

**Study Area and Its Existing Second-Order Soil Map**

This study was conducted in an agricultural landscape in a valley of the Northern Appalachian Ridge and Valley Physiographic Region in central Pennsylvania. The study area consists of a 19.5-ha agroecologic field at the Kepler Farm of the Pennsylvania State University (Fig. 1). Crops grown on this farm are corn (*Zea mays* L.), soybean (*Glycine max* (L.) Merr.), and winter wheat (*Triticum aestivum* L.) with rotational planting. Within this landscape, elevation ranges from 373 to 396 m. Depth to bedrock changes from <0.25 m on the ridgetop to >3 m on footslopes. The second-order soil map of the area developed by the USDA-NRCS identified five major soils—the Hagerstown, Opequon, Murrill, Nolin, and Melvin series (Fig. 1). The well-drained, deep (1.0–1.5 m) and very deep (>1.5 m) Hagerstown (a fine, mixed, semiactive, mesic Typic Hapludalf), and shallow (<0.5 m) Opequon (a clayey, mixed, active, mesic Lithic Hapludalf) soils formed from limestone residuum. The very deep, well-drained Murrill (a fine-loamy, mixed, semiactive, mesic Typic Hapludult) soil formed from colluvial materials derived from acid sandstones and shales and the underlying limestone residuum. The very deep, poorly drained Melvin (a fine-silty, mixed, active, nonacid, mesic Fluvaquentic Endoaquept) and well-drained Nolin (a fine-silty, mixed, active, mesic Dystric Fluventic Eutrudept) soils formed from aluvium washed from surrounding uplands with limestone underlying. On the second-order soil map, soils formed from limestone residuum (Hagerstown and Opequon–Hagerstown complex) occupy about 80%
of the total study area. Soils formed from colluvium (Murrill) and alluvium (Nolin and Melvin) occupy about 11 and <10% of the total area, respectively (Fig. 1). Five soil pits representing these five major soils were excavated to obtain full soil profile descriptions (Fig. 1).

Repeated Electromagnetic Induction Surveys

Georeferenced EMI surveys were conducted across the study area at various times using different meters, dipole orientations, and geometries. The first survey was conducted in January 1997 and used two meters, an EM38 operated in vertical dipole orientation (EM38V) and an EM31 (Geonics Ltd., Mississauga, ON, Canada) operated in vertical (EM31V) and horizontal (EM31H) dipole orientations. These pedes-
trian surveys, which were completed in the station-to-station mode using a 30-m grid, each resulted in 243 measurements. Subsequent surveys were made between 2006 and 2009 (Table 1) and were completed on a mobile platform (i.e., meters mounted on a sled and towed behind an all-terrain vehicle) with meters operated in the continuous mode. The second survey was completed in March 2006 with a Dualem-2 meter (Dualem Inc., Milton, ON, Canada) operated in both the perpendicular (EMPRP) and horizontal co-planar (EMHCP) geometries. The remaining six surveys were completed from January 2008 to April 2009 using the EM38V. All the surveys conducted on a mobile platform had
Table 1. The 95% confidence intervals of soil apparent electrical conductivity (ECa) in different soil series determined by the EM31 meter in vertical dipole orientation (EM31V) on 24 Jan. 1997, the Dualem-2 in horizontal co-planar geometry (EMHCP) on 22 Mar. 2006, the EM38 in vertical dipole orientation (EM38V) on 12 Nov. 2008, and the relative difference (δ) in ECa for all 11 electromagnetic induction (EMI) surveys. These 95% confidence intervals were based on the 145 soil core locations with their ECa values extracted from the interpolated ECa maps.

<table>
<thead>
<tr>
<th>Soil series</th>
<th>Soil cores</th>
<th>EM31V</th>
<th>EMHCP</th>
<th>EM38V</th>
<th>δ in ECa</th>
</tr>
</thead>
<tbody>
<tr>
<td>Opequon</td>
<td>48</td>
<td>(6.70, 7.80)</td>
<td>(7.47, 9.03)</td>
<td>(10.67, 11.94)</td>
<td>(−0.23, −0.12)</td>
</tr>
<tr>
<td>Hagerstown</td>
<td>63</td>
<td>(7.81, 10.11)</td>
<td>(9.16, 10.29)</td>
<td>(12.25, 13.60)</td>
<td>(−0.09, −0.04)</td>
</tr>
<tr>
<td>Murrill</td>
<td>17</td>
<td>(7.64, 9.88)</td>
<td>(11.25, 12.30)</td>
<td>(12.26, 17.42)</td>
<td>(0.05, 0.11)</td>
</tr>
<tr>
<td>Nolin</td>
<td>10</td>
<td>(10.65, 13.80)</td>
<td>(10.50, 13.08)</td>
<td>(12.31, 13.52)</td>
<td>(0.12, 0.27)</td>
</tr>
<tr>
<td>Melvin</td>
<td>7</td>
<td>(15.00, 16.54)</td>
<td>(16.43, 20.99)</td>
<td>(17.03, 19.74)</td>
<td>(0.45, 0.66)</td>
</tr>
</tbody>
</table>


d is a measurement density of approximately 3 by 8 m, yielding a total of >5400 data points each time. All ECa measurements were corrected to a standard temperature of 25°C using the formula derived by Sheets and Hendricks (1995). In our study area, the drier and coarser surface soil generally has lower electrical conductivity than the wetter and more clayey subsoils. As Callegary et al. (2007) observed, the lower surface soil electrical conductivity can reduce the drift of measurement depth of an EMI instrument, making repeated EMI surveys more comparable. The antecedent precipitation during 7 d preceding an EMI survey (API7) was used as an indicator of soil wetness in the study area before each EMI survey. Technical details on the meters, API7, and air and soil temperature during each survey and the procedures used for meter calibration and preparation can be found in Zhu et al. (2010).

**Soil-Landscape Data Collection**

For ground truthing of soil types and different soil properties, intact soil cores were extracted from 145 locations throughout the study area (Fig. 1). The procedures outlined by Lin et al. (2006) were used to obtain the intact soil cores with the aid of a hydraulic system mounted on a tractor. Unless restricted by shallow bedrock, intact soil cores of 0.038-m diameter were extracted to a depth of 1.1 m. Each core was identified as one of the soil series based on their morphological features. Overall, there were a total of 48, 63, 17, 10, and seven soil cores identified as the Opequon, Hagerstown, Murrill, Nolin, and Melvin soils, respectively (Table 1). Seventy of these 145 cores were then sampled by horizon for particle size distribution and organic matter content. The simplified method of Kettler and Doran (2001) was used to determine the particle size distribution. The organic matter content was measured using the loss-on-ignition method (Ball, 1964).

The depth-weighted average ($V$) of clay, silt, and organic matter contents within the top 1.1-m solum was calculated as

$$V = \frac{\sum HT_i \cdot \rho_i}{\sum HT_i}$$

where $HT_i$ is the thickness of the $i$th horizon, $\rho_i$ is the content of clay, silt, or organic matter in the $i$th horizon, and $n$ is the number of soil horizons.

Soil ECa readings collected from each EMI survey were interpolated using ordinary kriging in ArcGIS 9.1 to generate an ECa map for the entire study area. A map showing the relative difference (δ) of soil ECa among different locations was calculated from these interpolated ECa maps using the method of Vachaud et al. (1985). The relative difference showed the temporal stability of soil ECa, with positive and negative values indicating areas of higher and lower ECa, respectively, than the entire study area's overall mean. The related details of ECa map interpolation and relative difference calculation are provided in Zhu et al. (2010). The ECa values and the relative difference in ECa at the 145 soil core locations were extracted from the interpolated maps. These extracted values were statistically compared with various soil properties. Statistical analyses included a t-test, Spearman correlation, and multiple linear and nonlinear regressions, which were performed using SAS (SAS Institute, Cary, NC), with a significance level of $p < 0.05$.

The confidence limits for soil ECa values and their relative differences for all 11 EMI surveys were calculated for the different soils at the 95% confidence level using the extracted values at the 145 soil core locations (Table 1). In an EMI survey, if the 95% confidence intervals of soil ECa among different soils had gaps, the ECa values falling in these gaps were used to delineate transitional zones between the adjacent soils. For example, in the EMHCP survey, which was conducted on 22 Mar. 2006, small gaps in the 95% confidence intervals of ECa were observed between the Opequon and Hagerstown soils (Table 1). Therefore, in the EMHCP ECa map, areas with $ECa < 9.03$ were mapped as the Opequon, areas with $9.03 < ECa < 9.16$ were mapped as the transitional area between the Opequon and Hagerstown (labeled as the Opequon–Hagerstown variant), and areas with $9.16 < ECa < 10.29$ were mapped as the Hagerstown soil. In some of the EMI surveys, ECa confidence intervals overlapped between two or more soils. In that case, a complex of multiple soils was delineated as a lumped map unit.

Following this approach, soil maps were generated using the EM31V data collected on 24 Jan. 1997, the EM38V data collected on 12 Nov. 2008, and the relative difference in ECa calculated from all the EMI surveys. The first two maps were selected to illustrate a good and a bad scenario for using a single EMI survey to delineate soils. The relative difference in ECa calculated from all 11 EMI surveys was intended to maximize all ECa data collected using temporal stability (Vachaud et al., 1985) to delineate soils.

According to soil descriptions in the second-order soil survey, a key difference among the five soil series identified in the study area is depth to bedrock (with the Opequon's depth to bedrock <0.5 m, the Hagerstown's >1 m, and the Murrill, Nolin, and Melvin's >1.8 m). Therefore, a depth-to-bedrock map can be used to delineate the Opequon and Hagerstown soils and the transitional area between these two soils. Combining this information with the 95% ECa confidence intervals

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for the different soils (Table 1) and other attributes described below, a fourth refined soil map was developed in this study.

Regression kriging was used to generate a depth-to-bedrock map for the entire study area based on the 77 point observations (Fig. 2). A multiple linear regression equation was first developed by a stepwise process with $p < 0.15$ (meaning that if the $p$ value of a variable was $>0.15$, it was excluded from entering the regression equation). The final regression equation ($R^2 = 0.82$) incorporated three terrain attributes (elevation, slope, and profile curvature) and the ECa values from the EM31V survey as independent variables. The residuals of the regression were kriged and then subtracted from the regression to obtain the final regression kriging map for the depth to bedrock in the study area, which provided a reasonable accuracy compared with actual observations (Fig. 2). Details of the regression kriging procedures used can be found in Zhu and Lin (2010).

Furthermore, additional EMI survey results were utilized in the following specific ways in developing the fourth refined soil map:

1. A distinct difference between the Murrill and Hagerstown soils is their textures. The Hagerstown soils have <55 and <45% silt in their Ap and Bt horizons, respectively, while the Murrill soils have >65 and >70% silt in these two horizons, respectively (Fig. 1). Because the Murrill soils are only distributed on the south side of the ridgeline (see Fig. 1) based on parent material distribution and our soil core observations, the EMHCP survey (which had the best correlation with soil silt content) was used to separate out the Hagerstown and Murrill soils in the south part of the study area.

2. The EM31V survey results were used to delineate the Hagerstown, Nolin, and Melvin soils in the north part of the study area because the Nolin and Melvin soils are only distributed on the north side of the ridgeline (see Fig. 1) based on the second-order soil map and our soil core observations. Therefore, the deep-sensing EM31V was optimal in capturing the differences in depth to bedrock and the associated water table among these three soils.

**RESULTS AND DISCUSSION**

**Mapping Soil Properties through Repeated Electromagnetic Induction Surveys**

Depth to bedrock is an important criterion for differentiating soils in the study area. Therefore, we attempted to develop a map of depth to bedrock using relevant EMI surveys. The correlation between soil ECa and observed depth to bedrock at the 77 locations is shown in Fig. 3a for all the EMI surveys conducted. It is apparent that the EM31V survey conducted on 24 Jan. 1997 gave the best correlation ($r^2 = 0.58, p < 0.05$). This was because the EM31V provided the more appropriate profiling depth (0–6 m) and depth-weighted sensitivity, and thus was most suited for capturing the variation in depth to bedrock in the study area. The other meters, dipole orientations, and geometries provided measurement depth ≤3 m and less appropriate depth-weighted sensitivities, and thus were less effective in mapping depth to bedrock ($r^2 < 0.42$). By combining them with terrain attributes (elevation, slope, and profile curvature) through the selection of stepwise regression procedure, we used the ECa values from the EM31V survey to construct the optimal depth-to-bedrock map for the entire study area via regression kriging (Fig. 2).

The repeated EMI surveys were also examined for mapping soil textural variability. Through soil profile descriptions from the five excavated soil pits (one for each of the five soil series), soil horizons deeper than 2 m showed similar textures (clay loam or silty clay loam) except the shallower Opequon and Hagerstown...
soils. Thus, differences in texture were mainly observed in the top 2 m of the soil profiles (Fig. 1). The EM31H survey with a measurement depth of 3 m appears to explain a larger proportion of the variation in silt content \((r^2 = 0.45, p < 0.05)\) than the EM38V and EM31V surveys conducted at the same time but with measurement depths of 1.5 and 6 m, respectively (Fig. 3b). Similarly, the EMHCP survey, with a measurement depth of 3 m, also explained the silt content variation better \((r^2 = 0.47, p < 0.05)\) than the EMPRP with a measurement depth of 1.3 m (Fig. 3b). In comparison, the EM38V surveys conducted on 24 Jan. 1997 and 4 June and 12 Nov. 2008 explained the least variation in silt content \((r^2 < 0.30)\). These surveys were conducted during relatively dry periods with low API7 (1.8, 12.2, and 2.5 mm, respectively) (Fig. 3b), while soils with higher silt contents in our study area (e.g., the Nolin, Melvin, and Murrill series) were distributed at lower elevations generally associated with higher soil moisture. Furthermore, the relationship between soil ECa values and silt contents was the highest for the top 1.1-m solum, followed by the Bt horizons, and then the Ap horizons (Fig. 3b).

The \(r^2\) value between clay content and soil ECa was low throughout this study (Fig. 3c). Close and positive relationships between clay content and ECa have often been reported in the literature (e.g., James et al., 2003; Abdu et al., 2008; Harvey and Morgan, 2009) because higher clay content is often associated with higher water holding capacity and cation exchange capacity, leading to higher ECa. In our study area, however, soils with higher clay content in the top \(\sim 2\) m of the soil profile, especially the Bt horizons (e.g., the Opequon and Hagerstown soils, with clay content >20 and >40% in the Ap and Bt horizons, respectively), are distributed in areas with higher elevations and steeper and convex slopes and are thus relatively drier (Fig. 1). In contrast, deeper soils with lower clay content in the top \(\sim 2\) m of the profile (the Murrill, Nolin, and Melvin series, with clay content mostly <15 and <35% in the Ap and Bt horizons, respectively) are distributed along lower elevation areas associated with higher soil moisture contents (Fig. 1). Thus, it is possible that the differences in soil depth (depth to bedrock) and moisture distributions masked the effects of clay content as sensed by EMI in this study. For the same reason, slightly higher \(r^2\) values between clay
content and ECa were observed during drier periods (Fig. 3c). Another possible reason for the lack of correlation between clay content and soil ECa in this study is the fact that we used the simplified method of Kettler and Doran (2001) to determine the soil particle size distribution, where silt content was measured and clay content was calculated as the difference between 100% and the combined silt and sand contents, whereas, in most other studies, clay content was measured and silt content was calculated. Therefore, possible residue error in the calculated particle size could lead to reduced correlation with other soil properties.

Soil ECa has also been used to interpret the spatial distribution of total soil C (Gigera et al., 2006) and organic matter content (Omonode and Vyn, 2006). In the study conducted by Omonode and Vyn (2006), low ($r^2 < 0.43$) but significant correlations were found between ECa and organic matter content, especially in Mollisols and when the soil moisture content was higher. In our study, however, no clear relationship was found between soil organic matter content and soil ECa (Fig. 3d). This was probably because of the relatively homogenized organic matter distribution throughout the landscape due to frequent farm management practices.

**Mapping Soil Series through Repeated Electromagnetic Induction Surveys**

In all of our EMI surveys, the highest soil ECa was distributed in the northeastern corner, which was mapped as the poorly drained Melvin soils. The spatial distribution of the other four soils, however, as depicted on the second-order soil map, were not well correlated with actual ECa distributions in our EMI surveys (Table 2). By comparing them with the 145 soil cores examined, only 47.1% of them matched the soil series named in the second-order soil map units (Table 3).

In Table 2, the ECa values for the five soils based on the second-order soil map are statistically compared for each EMI survey. Generally, the mean ECa for the Melvin soils were the highest, while those of the Opequon soils were the lowest and those of the others (the Nolin, Hagerstown, and Murrill soils) fell in between; however, statistically significant ($P < 0.05$) differences in ECa between the Melvin and Opequon soils were not observed in the EM38V survey on 24 Jan. 1997 and the EMPRP survey on 22 Mar. 2006 (Table 2). These two EMI surveys had either the lowest API7 (1.8 mm on 24 Jan. 1997) or the shallower measurement depth (1.3 m for the EMPRP). This further suggests that EMI surveys conducted during drier periods or with shallow measurement depth could not adequately capture the spatial distribution of the soils in the study area. The differences in the range of ECa values between the Nolin and the Hagerstown, Murrill, and Opequon soils, and between the Opequon and Hagerstown soils were also not significant ($p > 0.05$) in most EMI surveys based on the second-order soil map (Table 2). This can be attributed to the relatively coarse and impure map units in the second-order soil map. Exceptions included the significant ($p < 0.05$) difference in ECa values between the Nolin and Hagerstown soils in the EM31V, EM31H, and EMHCP surveys and between the Murrill and Hagerstown soils in the EMHCP survey (Table 2). These EMI surveys all had deeper measurement depths of ≥3 m.

After comparing the second-order soil map and the ECa maps, we investigated how the EMI surveys could be used to enhance the mapping of the soils across the 19.5-ha landscape. The differentiation between the very deep Melvin and the shallow Opequon soils using ECa readings was obvious in our EMI surveys (Fig. 4). The separation among the Hagerstown, Murrill, and Nolin soils using ECa, however, was less clear-cut and changed with time and the EMI meter used. Overall, four out of the total 11 surveys (the EM31V in 1997, the EMHCP in 2006, and the EM38V in March and April 2008) provided the best possible scenarios to differentiate various soils based on soil ECa values (Fig. 4a). For example, the Murrill soil is located on footslopes, closer to our simulated subsurface flow paths (Zhu et al., 2010), and thus generally has wetter conditions than the higher lying Hagerstown soil. Therefore, the EM38V conducted in wetter periods (e.g., on 10 Mar. and 30 Apr. 2008) was better at capturing the spatial separation of these two soils (Fig. 4a). Compared with the Hagerstown soil, the Nolin soil typically has a deeper depth to bedrock and occupies lower lying and depressional areas that tend to receive runoff from adjoining slopes. Thus, the EMI surveys conducted with deeper sensing meters (e.g., the EM31V and EMHCP) or under wetter conditions (e.g., on 10 Mar. and 30 Apr. 2008) are better at capturing the spatial separation of these two soils (Fig. 4a). In general, within our study area, EMI appears to be more effective in mapping soils during wet periods.

Because EMI surveys using proper meters at favorable times of the year can reasonably capture the spatial distribution of soil properties and soil types, an appropriate EMI survey (both timing and meter setting) can be used to aid in the refinement of an existing second-order soil map. In doing so, tacit knowledge of soil–landscape relationships and supporting observations are needed to ground truth the EMI interpretations. Examples of EMI surveys that may or may not be used to refine a second-order soil map are illustrated in Fig. 4b and 4c. In Fig. 4b, the EM31V clearly differentiated the areas of the poorly drained Melvin soil from the well-drained Hagerstown, Opequon, and Murrill soils. There was also little overlap in ECa between the Nolin soil and the Hagerstown, Opequon, and Murrill soils. In contrast, the histogram curves of ECa obtained from the EM38V survey conducted on 12 Nov. 2008 (Fig. 4c) showed greater overlaps in the ranges of ECa for each of the five soils. The Nolin soil, for example, was largely indistinguishable from the Murrill, Hagerstown, and Opequon soils in this case.

Examples of reasonably good and bad scenarios for developing a refined second-order soil map based on a single EMI survey are illustrated in Fig. 5a and 5b, and their ground truthing results are shown in Table 3. The reasonably good EM31V survey had 69.6% accuracy in matching with actual soil cores (22.5% higher than the second-order soil map), while the EM38V conducted on 12 Nov. 2008 obtained only 35.3% accuracy when compared with actual soil cores (worse than the second-order soil map).
Table 2. Mean ± standard deviation and minimum and maximum values of soil apparent electrical conductivity for the five major soils identified on the second-order soil map. The values were determined from actual point data collected in each electromagnetic induction survey.

<table>
<thead>
<tr>
<th>Meter used†</th>
<th>Survey date</th>
<th>Melvin Mean ± standard deviation and minimum and maximum values of soil apparent electrical conductivity</th>
<th>Nolin Mean ± standard deviation and minimum and maximum values of soil apparent electrical conductivity</th>
<th>Murrill Mean ± standard deviation and minimum and maximum values of soil apparent electrical conductivity</th>
<th>Hagerstown Mean ± standard deviation and minimum and maximum values of soil apparent electrical conductivity</th>
<th>Opequon Mean ± standard deviation and minimum and maximum values of soil apparent electrical conductivity</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Mean Min. Max.</td>
<td>Mean Min. Max.</td>
<td>Mean Min. Max.</td>
<td>Mean Min. Max.</td>
<td>Mean Min. Max.</td>
</tr>
<tr>
<td>EM38V</td>
<td>24 Jan. 1997</td>
<td>9.2 ± 0.9 6.6 11.4</td>
<td>7.2 ± 1.2 5.2 10.5</td>
<td>7.7 ± 0.9 5.0 10.6</td>
<td>7.8 ± 1.7 2.4 14.1</td>
<td>7.1 ± 1.4 3.4 10.2</td>
</tr>
<tr>
<td>EM31V</td>
<td>24 Jan. 1997</td>
<td>15.5 ± 1.0 13.0 17.7</td>
<td>12.1 ± 1.8 7.4 16.9</td>
<td>9.5 ± 1.0 4.8 11.6</td>
<td>8.6 ± 1.2 4.3 13.0</td>
<td>7.6 ± 1.1 4.0 15.4</td>
</tr>
<tr>
<td>EM31H</td>
<td>24 Jan. 1997</td>
<td>11.0 ± 0.5 9.5 11.9</td>
<td>9.3 ± 1.0 5.1 11.0</td>
<td>7.9 ± 0.5 6.3 9.4</td>
<td>7.1 ± 0.9 3.6 10.6</td>
<td>6.5 ± 0.7 3.6 10.1</td>
</tr>
<tr>
<td>EMHC</td>
<td>22 Mar. 2006</td>
<td>18.3 ± 1.6 10.9 25.2</td>
<td>12.5 ± 1.1 8.1 19.5</td>
<td>11.3 ± 0.7 6.9 16.2</td>
<td>9.7 ± 0.7 3.7 14.9</td>
<td>9.2 ± 0.9 3.9 14.9</td>
</tr>
<tr>
<td>EMP</td>
<td>22 Mar. 2006</td>
<td>7.8 ± 1.7 4.5 11.5</td>
<td>5.7 ± 1.2 3.2 9.8</td>
<td>5.7 ± 0.8 2.2 9.2</td>
<td>4.9 ± 1.6 0.6 10.1</td>
<td>4.6 ± 1.7 0.1 9.2</td>
</tr>
<tr>
<td>16 Jan. 2008</td>
<td>31.1 ± 2.5 22.9 36.4</td>
<td>25.6 ± 2.0 21.7 31.7</td>
<td>25.8 ± 1.7 20.6 32.8</td>
<td>24.3 ± 2.1 13.1 35.4</td>
<td>23.5 ± 3.7 12.9 31.1</td>
<td>23.6 ± 2.7 14.8 31.6</td>
</tr>
<tr>
<td>10 Mar. 2008</td>
<td>17.8 ± 1.8 11.9 25.4</td>
<td>11.5 ± 2.1 7.5 18.7</td>
<td>14.8 ± 2.1 6.0 23.6</td>
<td>11.2 ± 2.1 1.4 25.7</td>
<td>9.6 ± 2.6 1.9 17.4</td>
<td>9.6 ± 2.6 1.9 17.4</td>
</tr>
<tr>
<td>30 Apr. 2008</td>
<td>24.7 ± 2.9 19.0 31.1</td>
<td>19.6 ± 1.8 14.4 25.9</td>
<td>19.5 ± 2.4 11.0 42.0</td>
<td>19.1 ± 3.7 8.6 45.3</td>
<td>17.9 ± 3.4 6.5 28.3</td>
<td>14.8 ± 2.6 1.9 17.4</td>
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<tr>
<td>4 June 2008</td>
<td>29.8 ± 3.1 23.8 36.0</td>
<td>23.9 ± 2.2 19.1 29.9</td>
<td>22.8 ± 2.6 13.8 31.3</td>
<td>23.8 ± 2.8 15.1 36.3</td>
<td>23.6 ± 2.7 14.8 31.6</td>
<td>12.2 ± 1.7 6.5 17.4</td>
</tr>
<tr>
<td>12 Nov. 2008</td>
<td>16.5 ± 1.6 9.9 22.1</td>
<td>12.7 ± 1.6 8.1 17.0</td>
<td>16.0 ± 1.6 7.2 22.3</td>
<td>13.1 ± 2.0 6.7 21.4</td>
<td>12.2 ± 1.7 6.5 17.4</td>
<td>14.4 ± 2.6 5.4 20.9</td>
</tr>
<tr>
<td>23 Apr. 2009</td>
<td>21.3 ± 1.8 14.4 28.7</td>
<td>15.0 ± 1.7 8.8 21.5</td>
<td>18.4 ± 1.7 10.7 23.8</td>
<td>15.3 ± 2.9 5.5 29.0</td>
<td>14.4 ± 2.6 5.4 20.9</td>
<td>14.4 ± 2.6 5.4 20.9</td>
</tr>
</tbody>
</table>

† The surveys were performed with the EM38 in vertical dipole orientation (EM38V), the EM31 in horizontal (EM31H) and vertical (EM31V) dipole orientations, and the Dualem-2 in horizontal co-planar (EMHCP) and perpendicular (EMPCP) geometries.

‡ For each date and survey, means of the five soil types followed by the same letter were not statistically different at P < 0.05 significance level.

Table 3. Accuracy comparison between the existing second-order soil map and four new soil maps generated from different uses of electromagnetic induction (EMI). The EM31 meter in vertical dipole orientation (EM31V) on 24 Jan. 1997 is an example of a good scenario for mapping soils using a single EMI survey, while the EM38 meter in vertical dipole orientation (EM38V) on 12 Nov. 2008 is an example of a bad scenario for mapping soils using a single EMI survey. The relative difference (δ) in ECa shows the accuracy of the soil map generated from the combination of EM31V, the Dualem-2 in horizontal co-planar geometry (EMHCP), and depth to bedrock.

<table>
<thead>
<tr>
<th>Soil map units</th>
<th>Area Matched soil cores Unmatched soil cores</th>
</tr>
</thead>
<tbody>
<tr>
<td>Second-order soil map</td>
<td>EM31V</td>
</tr>
<tr>
<td>Opequon</td>
<td>5.8</td>
</tr>
<tr>
<td>Opequon-Hagerstown variant</td>
<td>5.8</td>
</tr>
<tr>
<td>Hagerstown</td>
<td>10.1</td>
</tr>
<tr>
<td>Hagerstown-Murrill variant</td>
<td>NA</td>
</tr>
<tr>
<td>Murrill</td>
<td>2.1</td>
</tr>
<tr>
<td>Hagerstown-Nolin variant</td>
<td>NA</td>
</tr>
<tr>
<td>Nolin</td>
<td>1.1</td>
</tr>
<tr>
<td>Nolin-Melvin variant</td>
<td>NA</td>
</tr>
<tr>
<td>Melvin</td>
<td>0.4</td>
</tr>
<tr>
<td>Total</td>
<td>19.5</td>
</tr>
</tbody>
</table>

† NA, the Hagerstown and Murrill soils and their transition zones (labeled as variants in this study) were not mapped by the EM31V, thus the validation was not available. The same applies to the Nolin, Murrill, and Hagerstown soils and their transition zones mapped by the EM38V.
While the absolute values of ECa change with time, the relative difference in ECa within the whole landscape during certain time period may offer a useful way of refining a soil map. Through a standardization of ECa values to their corresponding means across the entire landscape, Zhu et al. (2010) showed that repeated EMI surveys can reveal some temporally stable features, which are helpful in delineating different soils across the landscape. In this study, we calculated the relative difference (δ) in ECa within the whole landscape for the 11 EMI surveys, and the 95% confidence intervals of these δ values are shown in Table 1 for the five soils. These δ values were then used to develop a refined soil map (Fig. 5c). The resulting soil map had a higher accuracy than the second-order soil map, with nearly 70% of the soil cores matched with the map (Table 3). This soil map is also considered better than the one generated from the EM31V survey because it provides a finer resolution of various soils in the study area (Fig. 5; Table 3).

To further develop a best possible refined soil map, information from EMI surveys and terrain attributes were combined. The depth-to-bedrock map was first developed from the combined EMI survey and terrain attributes (Fig. 2), which was then further combined with other specific ECa maps obtained from other EMI surveys (the EM31V and EMHCP) (Fig. 5d). The EMHCP was selected because of its best correlation with silt content (Fig. 3b) and the EM31V was used because it had the best correlation with depth to bedrock (Fig. 3a) and the observed water table (data not shown). The resulting fourth refined soil map achieved 87.1% accuracy based on the examined soil cores (Table 3), which was almost doubled in map unit purity compared with the accuracy of the second-order soil map (47.1%).

The above results show that, although repeated EMI surveys could capture the spatial distribution of soils, the combination of EMI surveys with terrain attributes could achieve the best possible mapping accuracy. In the study of Abdu et al. (2008), predictions of soil texture and water holding capacity were
also improved with the aid of EMI surveys and a DEM. With advances in airborne geophysical methods (Robinson et al., 2008), EMI survey over large areas may become more feasible in the future. Together with increasingly available high-resolution DEMs derived from LIDAR, the refinement of widely available second-order soil maps across different areas may help overcome the bottleneck of providing high-resolution soil maps for more reliable, spatially distributed environmental modeling and site-specific precision natural resources management.

**SUMMARY AND CONCLUSIONS**

Different EMI meters, dipole orientations, and geometries resulted in different depth-weighted ECa values, which reflected the variability of different soil properties at different depths. The EMI surveys with the deepest measurement depth (e.g., EM31V) yielded the best results for mapping depth to bedrock, while the EMI surveys with moderate measurement depth (e.g., EM31H and EMHCP) gave optimal results for mapping silt content in our study area.

The characteristics of the study area also influenced the effectiveness of EMI in capturing the spatial distributions of certain soil properties. The spatial variation in soil depth (depth
to bedrock) and moisture masked the spatial variation in clay content as sensed by EMI meters in our study area. The repeated EMI surveys also did not capture the relatively homogenized organic matter distribution in the study area.

Because the major soil types in the 19.5-ha agricultural landscape have distinct differences in depth to bedrock, texture, and moisture, the EMI surveys with proper meters and settings, plus favorable timing, yielded improved outcomes for differentiating major soil types in the study area. The comparisons among the soil maps generated from single EMI surveys, repeated EMI surveys, and a combination of EMI surveys with terrain attributes showed that EMI surveys alone were insufficient to obtain the best possible mapping of soils. Instead, a properly executed EMI survey, combined with terrain attributes, could be used to generate a much improved soil map, the accuracy of which was nearly doubled compared with the second-order soil map in this study.

The results from this study demonstrate that both the timing and the appropriate selection of an EMI meter and operation mode are important in mapping soil variability. The optimal use of EMI depends on targeted soil properties, landscape characteristics, a specific EMI meter and its dipole orientation and geometry, and the timing of the survey. Thus, for different targeted soil properties and area characteristics, the selection of a survey time and meter should be considered. For example, while the EM31V yielded the best result for mapping depth to bedrock in our study area, Bork et al. (1998) found that the EM38V was only slightly less effective than the EM31V in capturing <2-m depth to bedrock in their study area. For areas with even shallower bedrock (e.g., <1 m), the EM38V would be more suitable than the EM31H or EM31V. For possible EMI mapping of soil C, the influence of soil moisture on ECa should be minimized; thus an EMI survey conducted during a dry period may yield a better result, which has been demonstrated by Banton et al. (1997) and Reedy and Scanlon (2003). In contrast, for mapping subsurface hydrologic dynamics across the landscape, the use of EMI during a wet period is recommended, as demonstrated by Zhu et al. (2010).

Overall, repeated EMI surveys within the same landscape can reveal stable and dynamic subsurface features. By correlating EMI maps with terrain attributes and soil properties, this relatively inexpensive and convenient geophysical tool could help the refinement of existing second-order soil maps and provide more detailed spatial information about the subsurface heterogeneity that is often needed for distributed modeling of landscape processes and for precision agriculture and natural resources management.

ACKNOWLEDGMENTS

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REFERENCES


