Hydrological consequences of land-cover change: Quantifying the influence of plants on soil moisture with time-lapse electrical resistivity

Dushmantha H. Jayawickreme¹, Remke L. Van Dam², and David W. Hyndman²

ABSTRACT

Electrical resistivity of soils and sediments is strongly influenced by the presence of interstitial water. Taking advantage of this dependency, electrical-resistivity imaging (ERI) can be effectively utilized to estimate subsurface soil-moisture distributions. The ability to obtain spatially extensive data combined with time-lapse measurements provides further opportunities to understand links between land use and climate processes. In natural settings, spatial and temporal changes in temperature and porewater salinity influence the relationship between soil moisture and electrical resistivity. Apart from environmental factors, technical, theoretical, and methodological ambiguities may also interfere with accurate estimation of soil moisture from ERI data. We have examined several of these complicating factors using data from a two-year study at a forest-grassland ecotone, a boundary between neighboring but different plant communities. At this site, temperature variability accounts for approximately 20%–45% of resistivity changes from cold winter to warm summer months. Temporal changes in groundwater conductivity (mean = 650 μS/cm; σ = 57.7) and a roughly 100-μS/cm spatial difference between the forest and grassland had only a minor influence on the moisture estimates. Significant seasonal fluctuations in temperature and precipitation had negligible influence on the basic measurement errors in data sets. Extracting accurate temporal changes from ERI can be hindered by nonuniqueness of the inversion process and uncertainties related to time-lapse inversion schemes. The accuracy of soil moisture obtained from ERI depends on all of these factors, in addition to empirical parameters that define the petrophysical soil-moisture/resistivity relationship. Many of the complicating factors and modifying variables to accurately quantify soil moisture changes with ERI can be accounted for using field and theoretical principles.

INTRODUCTION

The terrestrial landscape of our planet is increasingly becoming fragmented. The associated alterations of earth’s critical zone (National Research Council, 2001) affect water and energy exchanges between the atmosphere and the terrestrial biosphere, with important consequences for humans. Significant areas of forest are being cleared in the tropics, and most native forests and grasslands in the Americas, Europe, and Asia were converted to agriculture during the last century (Houghton, 1994). The potential impact of such landscape transformations on water supplies is a primary concern for many communities around the globe (DeFries and Eshleman, 2004; Nosetto et al., 2005; Scanlon et al., 2007; Cuo et al., 2009). Interception and root-water access differ significantly among plant species, and large quantities of water can move from soil and groundwater to the atmosphere through transpiration (Wullschleger et al., 1998). Similarly, when high-water-demand species are removed or replaced by those that require less water, soil moisture and groundwater levels may increase (Sahin and Hall, 1996). With additional implications for surface runoff and soil evaporation, vegetation changes can potentially alter subsurface water dynamics. Attempts to quantify such alterations include local and distributed sensor networks deployed in the field and remote-sensing methods (Cosh et al., 2004). However, at the scale of individual plants or a field plot, the influence of vegetation on soil moisture and groundwater is often poorly characterized because of a lack of suitable methods to examine the subsurface with required detail.

Environmental geophysics provides an array of methods for which responses depend on porosity, fluid saturation, and other physical and chemical attributes of porous media. Geophysical techniques can characterize and monitor subsurface processes across a wide range of scales with minimal disturbance. As a result, such
methods can be very useful in ecohydrology to address questions of vegetation and water dynamics in the environment. For many in the ecological community, the subsurface remains a challenging frontier. Geophysicists, on the other hand, have dealt with the complexities of subsurface exploration for more than a century, with vast improvements in theory and field technologies over the last few decades.

Electrical resistivity imaging (ERI) is a geophysical method well suited to improve our understanding of vegetation and soil–water interactions. The dependence of electrical conductivity (reciprocal of electrical resistivity measured in ERI) on soil moisture (Amidu and Dunbar, 2007) and fluid salinity (Oldenburger et al., 2007) and the potential to monitor various subsurface processes (Daily et al., 1992; LaBrecque et al., 2004; Israil et al., 2006; Looms et al., 2008; Van Dam et al., 2009) are major reasons ERI has become popular within the hydrologic science community (Robinson et al., 2008). The ability to image and quantify soil-moisture changes at important spatial and temporal scales with minimal disturbance to the environment and the possibility to acquire data in difficult terrain are two additional advantages.

In this paper, we discuss theoretical and practical aspects of using ERI to monitor the shallow subsurface for evidence of vegetation-driven soil-moisture dynamics. In the context of a long-term monitoring study in Michigan, U.S.A., we provide a detailed description of field practices and strategies for successful acquisition, processing, and interpretation of ERI data for ecohydrology studies. Most water and nutrient extraction by plants is from the upper 2–3 m of the subsurface (Schenk and Jackson, 2002); this zone is also the most responsive to weather and climate variability. To distinguish and quantify vegetation-driven hydrological perturbations, consistent long-term ERI data-acquisition strategies need to be combined with independent observations of other environmental variables that also influence soil electrical conductivity. Soil temperature and pore-fluid conductivity, for example, may fluctuate by different amounts temporally and spatially, depending on canopy cover and water-use differences between plant communities. Electrical conductivity also depends on soil properties such as composition and texture, which may show significant variability along the length of ERI arrays. This requires using multiple petrophysical models to interpret a single data set for soil moisture or other parameters of interest.

Several of these issues and approaches to address them are discussed in this paper, along with practical insights for successful application of ERI to examine plants and land-use-driven water dynamics in the subsurface, a topic of significant importance for understanding natural and anthropogenic factors influencing water and energy cycling in the environment.

**APPRAOCH**

We collected electrical-resistivity and other environmental data at a site in south-central Michigan that has been equipped to characterize land-use-driven soil-moisture dynamics (Figure 1). The site has been monitored since October 2006, with resistivity data collected biweekly and with groundwater level, soil moisture, and soil temperature measured bihourly. Groundwater salinity has been measured biweekly since May 2008 (Figure 2). For soil-temperature measurements, we installed temperature sensors below both land covers at depths of 5, 10, 20, 40, 117, and 147 cm. Three groundwater observation wells at the site contained sensors for water-level and ground-water-temperature measurements. Soil moisture was measured with capacitance probes at 20- and 80-cm depths in both land covers. All sensors were offset from the resistivity line by at least 1 m.

Glacial tills are the dominant subsurface material in the region. Based on soil-texture observations in several boreholes at the site, the top 40–60 cm of subsurface along the chosen transect consists of clay loam, underlain primarily by medium- to fine-grained sand. The forest has been present at the site for more than 30 years, but the grassland was cleared from the forest approximately 10–15 years ago. The site receives approximately 750 mm of precipitation annually (Figure 2a), and the air temperature ranges from subfreezing in the winter to about 30°C in June. The deciduous trees reach maximum leaf cover in early to mid-June, followed by leaf senescence in late September. Soil moisture observed in the forest shows the effect of vegetation with consistently low moisture content from spring to fall compared to other times of the year (Figure 2b). The water table fluctuates between 2 and 4 m, with highest water levels occurring in early to mid-April, just before the onset of active photosynthesis by plants in early spring, and lowest water levels in late November, several weeks after leaf senescence in the forest (Figure 2e). Despite significant summer rainfall, the groundwater level mostly declined from early spring to late fall.

Soil temperatures show significant seasonal fluctuations; although increasingly damped with depth, fluctuations propagate to the water table. Soil temperature is also affected by vegetation type (Figure 2c). Sensors at 40- and 117-cm depths indicate that during summer months, when the tree canopy shades the ground, forest soils remain 1°C or more cooler than grassland soils. The trend reverses in winter, with slightly warmer soil temperatures in the forest, likely from a more stable snow pack that provided insulation. Electrical conductivity of groundwater measured in samples collected near the water table showed consistently higher (~100 μS/cm) conductivity below the forest relative to the grassland. Rainfall-recharge events increased the shallow groundwater conductivity below both land covers, but this effect was largest in the forest (Figure 2d).

For electrical-resistivity measurements, 84 evenly distributed 12-mm-diameter graphite rods were permanently installed along a

---

**Figure 1.** Aerial view of the study site with locations of the electrode array, observation wells, and soil moisture and temperature sensors that are located at least 1 m from the array. The grassland was being mowed when the photo was taken.
124.5-m array, centered on the forest-grassland boundary (Figure 1). There was only 80 cm of elevation change along the array, with the highest elevation in the grassland. The 30-cm-long electrodes, buried flush with the surface, reached below the regional winter frozen-soil depth according to our temperature measurements. The position of each electrode was surveyed using a Leica total station. To provide protection from potential surface damage, each electrode was covered with a partially cored 1000-cm³ wood block, resulting in electrode-to-ground contact between 10 and 30 cm depth. To maximize data-collection efficiency and limit electrode-to-cable connection problems, the electrodes were permanently wired to a central take-out location using insulated 24-gauge wire. For data collection, the take-outs were connected to a switchbox located midway through the electrode array. This setup eliminated electrode position errors and incorrect wiring or connectivity problems.

Resistivity data along the electrode array were collected using an eight-channel AGI SuperSting resistivity meter with an 84-electrode switchbox. The data were collected using a Wenner electrode configuration (Dahlin and Zhou, 2004) to take advantage of its high signal-to-noise ratio (S/N). Each measurement was repeated once to improve the S/N and to provide estimates of random measurement errors. When the two readings differed by more than 2%, the mea-

Figure 2. Time series of environmental variables measured at or near the study site in 2008: (a) daily precipitation and mean air temperature recorded at a weather station approximately 1.5 km from the field site; (b) averaged daily volumetric soil moisture in the forest at 20- and 80-cm depths; (c) soil temperature in the forest at 40- and 117-cm depths along with difference between the forest and the grassland temperatures at the same depths; (d) groundwater electrical conductivity from collected water samples after April; and (e) water-table elevations measured in grassland and forest observation wells. See Figure 1 for locations of sensors and wells. Data series discontinuities in (b) and (e) (dotted lines) result from instrument malfunctions.
surement was repeated. Repeat measurements were kept to a minimum to limit the overall survey time to approximately 3 hours.

To estimate the subsurface resistivity distribution, we inverted the data using EarthImager 2D tomographic software. Data points with repeat errors larger than 1% were omitted from the inversions. This criterion applied to an average of 0.2% (σ = 0.4%) of points per data set. Repeat errors did not correlate significantly with precipitation events, snowpack, or air temperature. The initial inversion step involved calculating a forward model based on the average apparent resistivity of the entire data set. We used a finite-difference mesh with a width of half the electrode spacing and a height of 75 cm and a half the electrode spacing at the surface, increasing by 10% for each deeper layer. The total mesh consisted of 182 x 28 cells, including eight padding cells added on either side of the line and to the bottom of the mesh. We then used an iterative Occam ϵ₂-norm smooth inversion (Constable et al., 1987) with a topographic correction to account for the gradual 80-cm increase in elevation along the electrode array from forest to grassland.

An initial subsurface-resistivity model derived from the data acquired is shown in Figure 3. The model reveals strong spatial links between resistivity and the overlying vegetation. In an earlier study at this site, Jayawickreme et al. (2008) demonstrate that these spatial differences can be correlated to effective rooting depth. However, potential spatial heterogeneities of soils, porewater conductivity, and temperature also contribute to the modeled resistivity contrasts. In the following sections, we discuss these effects in more detail.

Temporal resistivity changes and time-lapse inversions

A key objective of implementing long-term monitoring programs is to obtain insight into spatial and temporal changes of a set of variables of interest and the processes that drive their subsurface perturbations. Therefore, it is important to adopt approaches that can identify these changes correctly while minimizing the effects of environmental noise, data errors, and other factors.

Differences between data sets collected at different times can be computed in several ways (Loke, 2000; Labrecque and Yang, 2001; Kim et al., 2009). A relatively straightforward approach is to invert the data sets independently and subtract the resulting models to obtain the difference between them. Nonuniqueness of the individual inversions and the potential for small errors to mask actual subsurface resistivity changes have been cited as some potential drawbacks of this approach (Daily et al., 2005). However, some studies suggest that model subtraction is a better approach than data differencing before inversion (e.g., Miller et al., 2008).

In our study, we used a difference inversion scheme (Labrecque and Yang, 2001) to calculate the change in resistivity distributions in a monitoring data set with respect to the resistivity distribution of a single base data set. We determined the convergence of the inversion with a weighted data misfit (ℓ₂-norm). A Lagrangian multiplier and a damping factor were applied to regularize the inversion and to suppress the effects of small eigenvalues of the Hessian matrix, respectively. The inversion of monitoring data incorporates information from the base data set to derive estimates of differences between the two data sets (Daily and Owen, 1991). The resulting percent change in resistivity between the base data set and each monitoring data set was used in the subsequent computations. An advantage of this approach is that the resulting change estimates are less likely to be affected by spatial variability in soil characteristics along the electrode array. However, there can also be disadvantages, particularly the potential for error propagation in situations where random data errors are present. Such risks can be minimized by choosing a base data set with minimal data errors and appropriate inversion parameters.

Few published studies use time-lapse ERI to evaluate long-term seasonal processes in the shallow subsurface (Binley et al., 2002; Miller et al., 2008). Time-lapse ERI studies of induced perturbations such as tracer infiltration and contaminant flow typically use the starting condition prior to introducing the tracer as the base (e.g., Nimmo et al., 2009). However, in studies of seasonal processes, the baseline starting condition is ambiguous; thus, the selection of a base data set is less clear. To evaluate the potential implications of the base data-set choice in such situations, we difference-inverted a monitoring data set acquired in May 2008 with two distinctly different base data sets: one from a dry period in October 2006 with generally high ground resistivity across the site and a second from a period with high soil moisture and low ground-resistivity values in January 2008.

Difference inversion of the monitoring data set with the two base data sets and the same inversion settings resulted in two subsurface resistivity models for the monitoring data set. As shown in Figure 4, the choice of base data set had little impact on the final results. The largest discrepancies between different models occurred at higher resistivity values. The resulting differences in subsurface resistivity models have implications for moisture estimates. Mean moisture uncertainty that would result from choosing the dry or wet base data set is 0.02 cm³/cm³, with 90% of the data points having a difference smaller than 0.04 cm³/cm³ (Figure 4b).
Laboratory estimation of resistivity/water-content relationship

Information on soil texture and other bulk soil properties is necessary to transform the resistivity values to hydrologic quantities. For example, surface-conductance effects of clays strongly influence the bulk electrical conductivity of soils (Revil et al., 1998). Thus, the petrophysical relation between water content and resistivity can be markedly different for soils with and without clays. The bulk density, degree of compaction, and pore orientation are also often highly spatially variable in natural settings, creating heterogeneities in the bulk electrical conductivity of soils (Friedman, 2005).

To estimate water content from resistivity data, we conducted laboratory experiments with 12 soil samples collected from three boreholes along the electrode array where the groundwater observation wells are located (Figure 1). The samples were first oven dried at approximately 80°C for 24 hours to remove interstitial moisture. A 15 × 5 × 5-cm Plexiglas box, with terminals for current transmission and potential readings, was filled with the dried sample at the approximate dry bulk density of field soils to replicate the original porosity and was weighed. After resistance measurements were collected for the boxed sample, the sediment was removed from the box, mixed with roughly 5% volumetric deionized water, repacked into the box, and reweighed before collecting the next resistance measurement. Temperature was recorded before each measurement to correct for its influence on soil conductivity. This procedure was repeated until water content reached approximately 0.25 cm³/cm³, after which there was little change in resistance.

Throughout the experiment, sample volume was strictly controlled to minimize errors resulting from porosity changes. The soil-moisture/electrical-resistivity relationships from 12 samples of sand and clay loam show that in the moisture range typical for field soils (0.1–0.35 cm³/cm³; Figure 2b), the relationship is linear in the log-log domain for both soil types (Figure 5). The slope of the relationship is different for the two soil-texture groups but is nearly identical for samples of the same group (sand −1.51 ± 0.19, clay −0.87 ± 0.08). The range of intercepts shows that small differences in texture and composition can have large effects on the electrical conductance of the material. Although differences in intercepts would lead to consistent under- or overestimation of moisture relative to a representative resistivity/soil-moisture fit, differences in slope would result in uncertainties biased toward higher or lower moisture-content ranges. For cases where estimation of changes in soil-moisture content through time is the primary goal, a consistent slope is more important than the intercept.

Soil temperature and resistivity

Bulk resistivity is influenced by soil temperature (Sen and Goode, 1992), which commonly has significant seasonal and diurnal fluctuations. For example, during the summer growing season at our site, soil temperatures below insulating forest canopies are about 2°C cooler than below grasses (Figure 2c). Seasonal and diurnal temperature fluctuations are largest near the surface, which is also the zone of interest for vegetation/soil-water interactions. When comparing resistivity profiles from locations with different land-cover characteristics or when time-lapse comparisons are involved, temperature-induced resistivity variations may partially mask those related to hydrologic changes. To account for temperature effects, subsurface soil temperatures need to be measured for resistivity data-collection intervals. At long-term monitoring sites, this can be achieved by installing multilevel sensors to a depth where the seasonal temperature variations are small.

The influence of temperature on measured resistivity can be removed using several empirical models. We chose a relatively simple approach based on a linear model of the form (Sen and Goode, 1992)

\[ \frac{\rho_{\text{ref}}}{\rho_t} = m(t - t_{\text{ref}}) + 1, \]  

where \( \rho_{\text{ref}} \) is the resistivity at a reference temperature \( t_{\text{ref}} \) (usually 25°C) and \( \rho_t \) is the resistivity measured at temperature \( t \). The fractional change in resistivity per unit change in temperature \( m \) is known to be nonlinear at large temperature ranges. The \( m \) values may also depend on the soil type for the linear model. For correcting our field data, we used \( m = 0.018 \), representative of glacial till materials with a modified version of the above empirical model (Hayley et al., 2007) adopted for the observed 2°C – 20°C soil temperature at the study site. The temperature correction was applied after inverting the field-resistivity data using temperature measurements at 20-, 40-, and 117-cm depths and in the groundwater wells. Temperature was assumed to be a constant 10.25°C at 10 m depth (based on mean annual temperature in observation wells; 10.25°C ± 2°C). Figure 6 shows the percent change in measured resistivity between January and August 2008, with and without temperature correction of data sets. Significant changes are clearly evident in the observed resistivity differences as a result of temperature (Figure 6c), which could be misinterpreted as changes in moisture if temperature corrections were not available.

Dissolved solutes and resistivity

Bulk soil electrical conductivity is affected by dissolved solutes in the porewaters. Figure 2d shows measured groundwater conductivities in two observation wells at the study site. It identifies important temporal and spatial differences in dissolved solute concentrations that are related to climate and land-cover characteristics. Although the measurement frequency is not ideal for identifying short-term trends in salinity, the spike in late September appears to be related to a large precipitation event that flushed the solutes which had accumulated in the vadose zone down to the saturated zone. Although increasing the conductivity of the saturated zone, these infiltration events would reduce the salt levels in the vadose zone. Such transient behaviors make accounting for fluid-conductivity effects on measured bulk soil electrical resistivity very difficult in the vadose zone, where the water content is also variable. Accurate accounting for this

![Figure 5. Resistivity versus porewater content in log-log domain for (a) six sand and (b) six clay loam samples, measured in the laboratory.](attachment:image.png)
type of behavior would likely require coupling with a detailed flow and transport model that also incorporates root water uptake processes.

Another notable feature in the data is the seasonally consistent difference in groundwater conductivity between the grassland and the forest (Figure 2d). This difference is likely caused by higher canopy interception rates in the forest relative to grass, which causes the trees to use more of the available soil moisture and concentrates the salts in the remaining interstitial water. Although small, the spatial difference in groundwater conductivity is clear from the observation-well data (Figure 2d). This salinity difference is also apparent in the measured bulk soil electrical-resistivity transects across the ecotone below the water table (Figure 7). Above the water table in the forest, the bulk conductivities are lower, which suggests that the effect of lower soil moisture overwhelms the effect of fluid conductivity in terms of overall resistivity response.

**Deriving soil moisture from resistivity**

ERI-based moisture profiles for the 2006–2008 monitoring period were derived from the resistivity-difference inversions with (1) a base data set acquired in March 2007, (2) the petrophysical relationships between water content and resistivity obtained in the laboratory explained earlier, and (3) Archie’s equation (Archie, 1942):

$$S = \left( \frac{\rho_i}{\rho} \right)^{1/m},$$

where $S$ is saturation (volumetric water content/porosity) and $\rho_i$ is resistivity at saturation, obtained from 2007 field data by averaging the values below the water table for sand (71.53 ohm-m) and from the clay-loam layer when it was saturated after snow melt and significant precipitation (68.15 ohm-m). The $\rho_i$ value for sand is consistent throughout seasons and between years; the value for clay loam was obtained during a period of waterlogged soils and represents an upper bound. The value $\rho$ is resistivity from inversions; $m$ is the power law coefficient between saturation and resistivity from the laboratory tests (sand = 1.15; clay loam = 0.66). The data were corrected for vegetation-specific soil-temperature variations in time and space. We assumed the temperature to be laterally uniform below each land cover except for a 20-m-wide section of the grassland, which is shaded seasonally by the adjoining forest. There the temperature was linearly interpolated between measured forest and grassland values.

Figure 8 shows that the averaged moisture measurements at 20- and 80-cm depths in the forest, from capacitance probes, are reasonably approximated by the ERI-derived moisture estimates obtained

---

**Figure 6.** Percent change in resistivity (ohm-m) from mid-January to mid-August 2008 (a) without and (b) with temperature correction. Warmer colors indicate an increase in resistivity by August relative to January values. (c) The difference between the two panels (b minus a). (d) Measured vertical temperature profiles for January and August below both land covers.

**Figure 7.** Averaged bulk soil-conductivity profiles below the grassland (100–103 m) and the forest (35–38 m) in August 2008 show the likely influence of the observed groundwater conductivity difference (Figure 2d). The water-table depth was approximately 3 m at the time of resistivity-data collection.

**Figure 8.** Comparison between 2007 and 2008 (January to June) ERI-derived and probe-observed soil-moisture values. Observed data are averages from 20- and 80-cm depths in the forest. Data from times when either of the observation probes was malfunctioning are omitted.
by averaging the nine cells in the inversion closest to the moisture probes ($R^2 = 0.9$). The ERI-derived moisture, however, is consistently underestimated compared to the capacitance probes. Several factors likely contribute to this observed discrepancy, including the shallow and sharp soil-texture change at approximately 60-cm depth from clay loam to sand. Among others, the capacitance probes are only sensitive to moisture changes in a small region surrounding the probe; the ERI is sensitive to a larger volume.

The spatial resolution of resistivity images depends on the electrode geometry and configuration used in the field as well as on resistivity inversion procedures. The resolution also decreases with depth and may depend on the instrument’s capabilities. Uncertainties related to moisture-probe calibration, resolution of temperature sensors, variability in salt concentration, soil disturbance during sensor installation, errors in measured water-content/resistivity relationships, and the selection of $p_s$ may all contribute to the discrepancy between observed and calculated soil-moisture values. The strong correlation of probe-measured and ERI-derived values, however, is an indication that the ERI estimates are sufficiently accurate for quantitative temporal and spatial analysis of soil moisture.

**DISCUSSION**

In our study, we adopted field practices that generated high-consistency data while maintaining the natural site conditions. This is particularly useful for studies that attempt to examine hydrologic changes from plant processes where changes are often subtle. Permanent installation of electrodes that are wired to a central location essentially eliminated potential electrode mislocation errors between measurements and significantly reduced the time spent setting up the site for data acquisition. Permanent installation also minimized the disturbance of vegetation, which was particularly important in the grassland during the growing season and across the entire site during periods with snowpack. Burying the electrodes below the surface also prevented contact-resistance problems that would have been otherwise likely during dry summer periods with significant soil-water evaporation.

The research presented in this paper shows that covariability of soil temperature, porewater saturation, and porewater salinity in natural settings presents some challenges to using ERI for quantifying soil moisture. Soil temperature is potentially the most important variable because of the strong influence it has on bulk soil electrical conductivity. However, temperature can be measured and its influence on resistivity measurements can be confidently accounted for with simple empirical models. Incorporating the influence of salinity changes, on the other hand, is complicated by the complex relationship between salts, saturation, soil texture, and bulk resistivity. Existing petrophysical models in that regard are limited and difficult to apply in unsaturated settings. The spatial variability of soil temperature and salinity is difficult to capture with sufficient detail, especially for ERI transects hundreds of meters in length. However, for our site, which is typical for temperate conditions, the effect of temperature and salinity on resistivity is less than that of soil-moisture variations. Thus, although some error inevitably will be introduced into ERI-estimated values, the soil-moisture variability dominates the results.

In the absence of universally applicable petrophysical models, estimation of soil moisture from electrical resistivity data requires site-specific resistivity/saturation measurements. Although laboratory methods are available for developing these models, several factors can introduce small errors into final moisture estimations. For example, alteration of porosity, soil structure, and pore connectivity during laboratory experiments can affect the soil electrical conductivity characteristics. An appropriate saturated resistivity value can be determined from field resistivity data below the water table. Alternatively, an upper bound for the saturated resistivity value can be obtained during the wettest periods. An evaluation of potential implications of a $\pm 10\%$ difference in selected $p_s$ shows that the error in computed water saturation would be larger for clay loam ($\pm 14\%$) than for sand ($\pm 8\%$) (Figure 9). For both soils, the absolute difference of the estimates is larger closer to soil-water saturation and decreases with decreasing water content or increasing resistivity.

When seeking quantitative information from ERI data, it is important to determine whether a subsurface resistivity model generated through inversion is representative or realistic for a given site. This requires knowledge of the site’s sediment architecture, hydrology, and other characteristics that have an influence on electrical conductance. Systematic and random noise from instrument and environmental sources can lead to erroneous interpretations. When such factors are properly accounted for, it is possible to monitor subtle changes in moisture content and other variables of interest.

**CONCLUSION**

This study demonstrates that ERI can be a useful tool for imaging dynamic soil-moisture variations in the shallow subsurface. The dependence of electrical resistivity on soil moisture, which in turn is related to vegetation and climate processes, enables the use of ERI for ecohydrological studies. The ability to measure these moisture variations at scales from less than one to hundreds of meters eliminates some of the deficiencies of using point sensors and offers new possibilities for quantifying detailed soil-moisture dynamics from plot to watershed scales. The relative ease of data collection combined with simple field strategies to improve data quality and consistency can substantially improve the quality of information that can be obtained.

The covariability of soil moisture, porewater salinity, and soil temperature in natural settings can complicate efforts to derive information on a particular system state. These can be accounted for with site-specific petrophysical models that can also address soil texture and composition. The need to invert the data to obtain a subsurface resistivity model adds uncertainty and potential error to final hydrologic quantities obtained. Nonuniqueness of the inversion process is a particular concern in this regard. Smoothing and other data-fitting
strategies during inversion along with factors such as loss of resolution with depth may limit the ability to observe processes at fine scales and resolutions. Despite these drawbacks, ERI provides an efficient way to visualize moisture dynamics of the critical zone, driven by the interplay of climate and vegetation.

ACKNOWLEDGMENTS

This research was funded by the U.S. National Science Foundation (NSF) (EAR-0911642) and the Michigan State University Center for Water Sciences. Any opinions, findings, and conclusions or recommendations expressed in this publication are those of the authors and do not necessarily reflect the views of the NSF. We thank P. Bloose and R. Kleivickas for access to the site; M. Dogan, K. Diker, A. Norton, and B. Eustice for assistance with data collection; and three anonymous reviewers for helpful suggestions that improved the manuscript.

REFERENCES


