A New Electromagnetic Induction Calibration Model for Estimating Low Range Salinity in Calcareous Soils

Xystus N. Amakor*
Grant E. Cardon
Plants, Soils & Climate Dep.
Utah State University
Logan, UT 84322-4820

Jürgen Symanzik
Mathematics and Statistics Dep.
Utah State University
Logan, UT 84322-3900

Astrid R. Jacobson
Plants, Soils & Climate Dep.
Utah State University
Logan, UT 84322-4820

In arid and semiarid regions, calibrating bulk soil salinity sensing technologies such as electromagnetic induction (EMI) relies on the assumption of uniformity of all soil factors influencing the reading, except soil salinity, to create a calibration model. When potentially perturbing factors are non-homogeneous or interact in a non-systematic way, conditional mean calibration models based on the least squares method fail to completely describe the entire salinity distribution due to the violation of model assumptions (i.e., homogeneity of perturbing factors). Therefore a new approach is needed. The main objective of this study is to produce a salinity calibration model capable of reasonably predicting salinity directly from the EMI signal readings irrespective of the heterogeneity of perturbing factors. Toward this end we collected ground-truth samples and corresponding EMI measurements in 35 agricultural fields covering 495 ha of the Irrigated Middle Bear (IMB) subbasin of Cache County in Utah. Using quantile regression (QR), which makes no assumption about the distribution of error, we estimated a subset of conditional quantiles of salinity as a function of EMI reading. We found that the mean effects estimated by previous models are misleading because they model behavior around the 0.9th quantile of the distribution, and thus grossly underestimate salinities in the lower quantiles. We developed a new EMI weighting procedure to account for the high heterogeneity that may have caused the upper-tailed distributional behavior. Variability was effectively captured and well modeled at specified quantiles of the salinity distribution using the QR technique. Independent validation of selected multiple QR models indicates that at low salinity ranges corresponding to conditional quantile (τ) $\leq$ 0.25, the QR models may be applied to any soil with low range salinity.

Abbreviations: CEC, cation-exchange capacity; ECa, apparent electrical conductivity; EC_H, bulk electrical conductivity readings measured in the horizontal modes of operation; EC_{H25}, horizontal apparent electrical conductivity that is depth-weighted based on the theoretical depth response curve and corrected to the reference temperature 25ºC; EC_{H25ECe}, horizontal apparent electrical conductivity that is depth-weighted based on the ECe profile ratios and corrected to the reference temperature 25ºC; EC_V, bulk electrical conductivity readings measured in the vertical modes of operation; EC_{V25}, vertical apparent electrical conductivity that is depth-weighted based on the theoretical depth response curve and corrected to the reference temperature 25ºC; EC_{V25ECe}, vertical apparent electrical conductivity that is depth-weighted based on the ECe profile ratios and corrected to the reference temperature 25ºC; ECe, electrical conductivity of the saturation paste extract; EMI, electromagnetic induction; MLR, multiple linear regression; IMB, Irrigated Middle Bear; MSE, mean square error; MSPE, mean squared prediction error; OLS, ordinary least squares; QR, quantile regression; SLR, simple linear regression; TC, total carbon; TIC, total inorganic carbon; TOC, total organic carbon τ, conditional quantiles.

The EMI sensing technique is a rapid, efficient, nondestructive field-based method of assessing soil salinity. The EMI sensor (e.g., the EM 38-DD from Geonics Inc., Mississauga, ON) measures the apparent electrical conductivity (ECa) of soils in both the vertical (EC_V) and the horizontal (EC_H) modes of operation, as a function of soil properties such as soil salinity, moisture

Soil Sci. Soc. Am. J. 77:985–1000
doi:10.2136/sssaj2012.0320
Received 25 Sept. 2012
*Corresponding author (xystus.amakor@aggiemail.usu.edu).

content, clay content, clay mineralogy, bulk density, pore-size distribution, cation composition, cation-exchange capacity, and temperature (Corwin and Lesch, 2005). Soil salinity is a dominant property sensed by the EM38-DD meter in soils of the arid and semiarid regions, and it is also a commonly important property of irrigated agricultural soils in these regions (Corwin and Rhoades, 1982, 1984; Lesch et al., 1995; Rhoades, 1992; Rhoades et al., 1999). Monitoring soil salinity requires the calibration of remotely sensed ECa signal readings with the traditional laboratory standard measure of salinity based on the electrical conductivity of the saturation paste extract (ECe; U.S. Salinity Laboratory Staff, 1954). However, the ECe measurement approach is too costly and time-consuming for detailed field inventories and monitoring of soil salinity. These can adversely affect the construction of a reliable ECe–ECa calibration model considering the large number of ground-truth samples required. Lesch et al. (1995) suggest a minimum of 6 to 12 sample sites for a spatial regression model. Geostatistical approaches based on the residual maximum likelihood variogram recommends around 50 samples (Kerry and Oliver, 2007) and 100 to 150 samples when using the method of moments variogram (Webster and Oliver, 1992).

Where soil salinity is the dominant factor affecting ECa, calibration models have been developed (Corwin and Rhoades, 1982; Wollenhaupt et al., 1986; McKenzie et al., 1989; Johnston et al., 1996; Triantafilis et al., 2000). These calibration models are based on single fields where possible contributions from other factors affecting ECa are considered negligible because their values within the fields are assumed to be uniform. The ECa depth-response relations of such homogenous profiles have been well defined (McNeill, 1980; McKenzie et al., 1989; Rhoades, 1992), and several attempts to address regional scale multi-field calibrations using the EMI signal readings have assumed homogeneous profiles (Harvey and Morgan, 2009; Wittler et al., 2006; Nogués et al., 2006). However, the theoretical depth response proportions developed for partitioning the bulk EMI signal readings into multiple depth measures for homogeneous profiles have been shown not to hold in non-homogeneous profiles (Rhoades et al., 1999).

Unlike the simple and well-defined, nonlinear depth response relation describing homogeneous profiles, heterogeneous profiles are complicated by irregular interactions of soil processes and confounding factors such that the depth-weighted ratios required to partition the bulk profile EMI signal reading are different and unknown at every location in the field. Clearly, accurate monitoring of salinity at a subbasin or watershed scale in such heterogeneous profiles should consider developing a user-defined or custom method for partitioning the bulk EMI signal reading to account for non-homogeneity.

Using either McNeill's theoretical depth response curve (McNeill, 1980) or directly using the bulk ECa, several within-field salinity calibration model functions have been developed over time. These models include the established coefficient model (Corwin and Rhoades, 1982, 1984), a simple linear model (McKenzie et al., 1989; Johnston et al., 1997), the modeled coefficient model (Slavich, 1990), a multiple linear model/spatial regression model (Lesch et al., 1995), a logistic profile model (Triantafilis et al., 2000), and the exponential decay profile model (Yao et al., 2007). Each model has its pros and cons. For example, Johnston et al. (1997) reported that the established coefficient and the modeled coefficient models incur more errors than models that predict ECe directly from ECa. Triantafilis et al. (2000) found that the fit of the salinity profiles were locally erratic using the established coefficient approach, probably due to weak assumption of this approach (i.e., assuming that theoretical ECa depth response functions hold for both homogeneous profiles and non-homogeneous profiles) and because of the semi-empirical nature of the model (i.e., the model employs both theoretical ECa depth response functions and ECa measurements). Wittler et al. (2006) when exploring the degree of accuracy associated with predictive equations that relate ECa to ECe measured over a 5-yr period on large fields (>61,000 ha), found considerable prediction uncertainty with their ECe–ECa calibration model. It should be pointed out that the sampling design, number of calibration samples, predominant ions in the soils, and the range of observed ECe, among other things, greatly affect the choice and accuracy of a model function used to calibrate the ECa for salinity interpretation. But one thing common to these proposed approaches and models is that a single best-fit conditional mean line is modeled through the data, usually by an ordinary least squares (OLS) regression method. The validity of parameter estimates from the OLS regression method is highly dependent on distributional assumptions such as normality and homoscedasticity. Because it is the intention of this article to present a salinity calibration model that fully describes the direct relationship between the EMI signal readings and ECe at every level of the soil salinity distribution, an appropriate technique other than the regular conditional mean regression approach needs to be developed.

We propose the use of quantile regression (QR) to address this question. The QR developed by Koenker and Bassett (1978), has been applied in ecological studies (Cade and Noon, 2003; Cade, 2011), econometrics (Koenker and Hallock, 2001; Koenker, 2005; Canay, 2011), clinical and genetic studies (Logan et al., 2012), biometrics (Burgette and Reiter, 2012), hydrology (Francke et al., 2008; Haddad and Rahman, 2011) and growth charts and health studies (Chen, 2005; Wei and He, 2006). Yet, QR has not received any attention in the field of soil science. Quantile regression offers the advantage of estimating the conditional distribution of a response variable over the entire support of its distribution (Koenker, 2005). This allows us to uncover the effect of covariates (such as the ECa) at different points on the conditional distribution of the response variable (e.g., the ECe). Quantile regression is able to detect changes in the shape of the conditional distribution of the response across the predictor variables and can therefore explain heteroscedastic data behavior and extend the modeling of a distribution beyond the conditional mean to a complete set of conditional quantiles (Pires et al., 2010; Koenker and Bassett, 1978). Essentially, our main objective is to present a more robust ECa–ECe calibration model that reveals a complete relationship between these variables across the entire soil salinity distribution in a region. We developed the model with soils in the IMB subbasin of Cache County, Utah and validated the model with soils in the Pariette Watershed in the Uintah Basin of Utah. The method developed should be extendable to other regions or basins with calcareous soils and low range salinity.

MATERIALS AND METHODS

Study Site

This study was conducted on 495 ha of arable land in 35 fields of the IMB subbasin of Cache County (central coordinates: 41° 54′8″ N, 111°56′6″ W), Utah. The study fields were selected based on irrigation water-use from the Bear River. Fields in the northern portion of the study area draw irrigation water directly from the Bear River, whereas tributaries of the Bear River are used to irrigate the southern half (Fig. 1). The climate is semiarid with a mesic soil temperature regime and xeric soil moisture regime. Moderate variation exists. The mean annual air temperature is 7.6 to 10.1° C and the annual precipitation is 416 to 490 mm across the study area. The topography of the area is relatively flat to slopes of up to 4% without microrelief, at an elevation ranging between 1345 and 1510 m above sea level. Major crops in the surveyed area are alfalfa (*Medicago sativa* L.), corn (*Zea mays* L.), small grains, peas (*Pisum sativum*), and pasture in rotation.

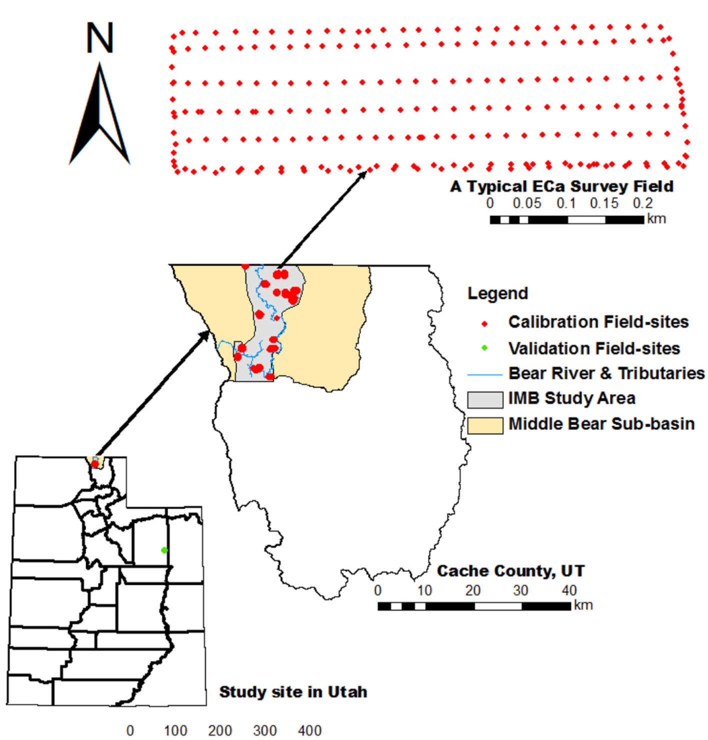

Fig. 1. The location of study area in the Irrigated Middle Bear (IMB) subbasin, Cache County, UT with 35 selected fields that draw irrigation waters directly from the Bear River in the northern portion and from the tributaries of the Bear River in the southern half. Also shown is an irrigated agricultural field of the Pariette watershed in eastern Utah that was used to validate the IMB salinity calibration models.

Soil Description

The soil texture classes range from sandy loam to clay. Trenton silty clay loam and Quinney silt loam are the most frequent soil series in the southern part of the site, while Lewiston and Kidman fine sandy loams dominate in the northern part (Fig. 1). Table 1 presents the soil map units and corresponding soil orders to family level based on the United State Department of Agriculture (USDA) soil classification scheme. The dominant soil order is Mollisols with the most common diagnostic subsurface features being calcic horizons and, to a lesser extent, natric or argillic horizons (Table 1). Other soil orders include Entisols (2% of the study area) and Aridisols with salic horizons (0.3% of the study area) (Table 1). All the soils are calcareous with a long history of irrigation. The parent material from which the soils formed are lacustrine deposits derived from either limestone and sandstone, or quartzite.

Apparent Electrical Conductivity Survey

On all 35 fields surveyed, ECa readings were measured in two dipole orientations (vertical: EC_V; and horizontal: EC_H) using a Geonics EM38-DD device (McNeill, 1980) during the summer and fall seasons from 2007 through 2009. Electromagnetic induction sensing was chosen for field-scale measurements of salinity because ECa responses can be obtained nondestructively and instantly from soils (Rhoades et al., 1999). Along transects of approximately 30-m intervals, the sensor was mobilized to take measurements. Whereas the ECa measuring system was towed on the soil surface by an all-terrain vehicle on large fields (>40 ha), it was hand-carried and placed on the soil surface at the measurement points on small fields (<40 ha). In both

Table 1. The area occupied by each of the soil series of the IMB subbasin study sites and their USDA classifications to the family level (Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture., 2004).

Field size, ha	Dominant soil series and surface texture	USDA soil classification to family level
22	Timpanogos Silt Loam	Fine-loamy, mixed, mesic Calcic Argixerolls
84	Trenton Silty Clay Loam	Fine, mixed, mesic Typic Natrixerolls
92	Kidman Fine Sandy Loam	Coarse-loamy, mixed, mesic Calcic Haploxerolls
171	Lewiston Fine Sandy Loam	Coarse-loamy, mixed, mesic Aeric Calciaquolls
52	Quinney Silt Loam	Coarse-silty, mixed, mesic Typic Natrixerolls
29	Avon Silty Clay Loam	Fine, montmorillonitic, mesic Calcic Pachic Argixerolls
8	Collett Silty Clay Loam	Fine, mixed, active, mesic Aquic Calcixerolls
7	Cache Silty Clay Loam	Fine, mixed, superactive, mesic Typic Aquisalids
18	McMurdie Silt Loam	Fine, montmorillonitic, mesic Calcic Pachic Argixerolls
12	Mixed Alluvial Land	Entisols

cases, measurements were made approximately every 30 m. The bulk raw conductivity values were directly recorded to a datalogger (Allegro Cx Juniper Systems Inc.) in millisiemens per meter (mS m^{-1}), together with their corresponding GPS positions that were read from a Trimble GPS connected at the center of the sensor measuring system. Following the standard calibration protocol of the EMI sensor in these deep agricultural soils, the instrument explored and measured vertically to a 1.5-m depth and about 0.75 m in the horizontal dipole position (Rhoades et al., 1999; Sudduth et al., 2001; Robinson et al., 2004; Corwin and Lesch, 2005; Nogués et al., 2006; Abdu et al., 2007). In total, over 30,000 ECa measurements were taken across the entire study area.

Soil Sampling Design

Soil samples collected on the same days as the ECa survey were based on the spatial pattern of the ECa pre-map. Seventy spatially referenced ground-truth soil samples were randomly collected in two to eight locations of low, medium and/or high ECa strata in each field to provide a basis for soil salinity calibration and monitoring. The calibration sampling locations were representative of the observed within-field variability in the ECa profile ratio data (Corwin and Lesch, 2005), as well as representative of all the landscape positions and soil map units in the field. At each of the calibration points, soil samples were collected at 0.3-m increments from the surface to a depth of 1.5 m, totaling 350 soil samples. Samples for gravimetric moisture content determinations were collected, and soil temperature was measured in situ at the calibration locations to compensate for temperature variation across and within profiles. The soil samples were air-dried, ground to pass a 2-mm sieve, and then used to prepare saturation paste extracts for the ECe measurements required for calibrating the remotely acquired ECa data.

Saturated Paste Extract Preparation and Characterization

Soil saturation paste extracts were prepared according to the method of Rhoades (1996), and selected soil properties (such as ECe, total dissolved organic carbon [DOC], and saturation percentage [SP]) were determined from the extracts. The ECe was first measured from a subsample of the saturation paste extracts using an automatic temperature compensating probe set to 25°C connected to an Accumet XL 30 conductivity meter (Fisher Scientific, CA). The pH of the same subsample was measured using an Orion combination pH electrode and pH meter, model-720A (VWR Scientific, CA). The ECe was measured before pH to avoid contaminating the extract with potassium chloride and producing erroneous ECe measurements. The DOC content of the soil extracts was measured using the Tekmar Dohrmann Phoenix 8000 (Teledyne Tekmar, Mason, OH).

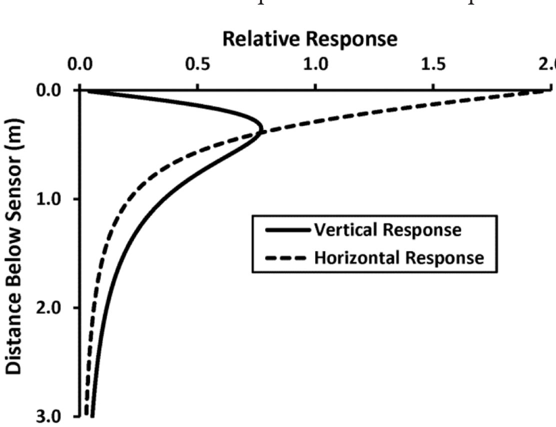

Fig. 2. Relative response of EM38-DD sensor as a function of distance (McNeill, 1980).

Soil Sample Analysis

The air-dried <2-mm soils were analyzed directly for particle-size distribution, total carbon (TC), total inorganic carbon (TIC), and total organic carbon (TOC) concentrations, and cation-exchange capacity (CEC). The particle-size distribution was determined by the hydrometer method (Gee and Bauder, 1986). Total C and TIC were determined sequentially from soil samples ground to < 246 μm. Total C was measured by combustion and TIC by phosphoric acid addition followed by non-dispersive infrared (NDIR) detection. Total organic C was then calculated automatically by difference (PrimacsSLC, SKALAR, Buford, GA). The CEC was determined using a modification of the unbuffered salt extraction method described by Sumner and Miller, (1996).

Data Analysis

Soil profile comparisons of selected soil properties that influence the EMI signal reading were characterized. Both dipole modes (EC_H and EC_V) of the EMI signal reading were utilized in three forms to produce calibration models:

i) by using the raw bulk EMI values, denoted as EC_H and EC_V.

ii) by using the theoretical depth response curves meant for homogenous profiles to depth-weight the EC_H and EC_V values (McNeill, 1980), with an assumption that it is equally applicable to heterogeneous profiles. The McNeill (1980) depth response curve defines the relationship between the EM38 response to soil conductivity (EC_V and EC_H) and soil depth (Fig. 2). The relationship is nonlinear and defined for homogeneous soils. This nonlinear depth response function defined by asymptotic approximations of the Maxwell's equations, is used to depth-weight the EC_V and EC_H. McNeill (1980) found that 22% of the signal response for the vertical dipole (EC_V) comes from 0 to 0.4 m of the soil profile and 78% from below this depth. For the EC_H, it was 53 and 47%, respectively. Rhoades and Corwin (1981) then derived fixed proportions to weight the EC_V and EC_H data to partition it into incremental layers, 0.3 m thick, in homogeneous soil profiles. The contribution percentages in the horizontal orientation are 43, 21, 10, 6, and 20 for soil depths 0 to 0.3, 0.3 to 0.6, 0.6 to 0.9, 0.9 to 1.2, and >1.2 m, respectively. Corresponding percentages in the vertical orientation are 17, 21, 14, 10, and 38, respectively.

iii) by using a weighting system based on observed ECe profile values to partition the EC_H and EC_V values. The ECe weights were calculated for each i (= 1,..., 5) observed ECe of five sample depths (0.3, 0.6, 0.9, 1.2, and 1.5 m) belonging to a particular profile j,(= 1, ..., 70) as follows:

$$\frac{ECe_{ij}}{\sum_{i=1}^{5} ECe_{ij}}.$$

These depth-partitioning ECe weights of the five depths were multiplied by their bulk EC_H and EC_V values. These ECe depth-weighted signal readings accounting for non-homogeneity of the profile salinity were then corrected to a reference temperature of 25°C (U.S. Salinity Laboratory Staff, 1954), and hereafter denoted as EC_{H25ECe} or EC_{V25ECe}, depending on the dipole orientation of the EM38. Similarly, the previously calculated ECa depth-weighted values were adjusted to the reference temperature and then denoted as EC_{H25} or EC_{V25}. Depth-weighting intervals for the EMI signal readings corresponded with the ground-truth sampling depths. To address our study objective of a detailed soil salinity calibration model, we examined three previous approaches (simple linear models, multiple linear models, and spatial regression models with transformed variables and a trend surface), in addition to the newly proposed quantile regression model. The QR modeling was performed with R software (R Development Core Team, 2012; ver. 2.15.0) using the quantreg package (Koenker, 2012).

The adjusted R^2 statistic, which accounts for the number of predictors used in the model, rather than the regular R^2 values, which do not, together with a 'pseudo' R^2 statistic (Koenker and Machado, 1999) were the goodness-of-fit parameters used for model selection for conditional mean models and QR models, respectively. Selections were made between log-transformed and untransformed models, as well as among models with different forms of the EMI signal readings. In addition to the results of the t-statistic for the significance of the parameter estimates, the Wald test and the likelihood ratio test were computed for estimates of the conditional quantiles.

The models were validated to check for the stability of the regression coefficients, the predictability of the regression function, and the ability to generalize inferences drawn from the regression analysis by using an independent test data set ($N = 42$) from an irrigated agricultural field in another watershed—the Pariette in the Uinta Basin, UT. To account for non-homogeneity in the soil salinity profile of the Pariette validating field, new ECe profile ratios were calculated and used to depth-weight the EMI data as previously described for the Cache County soil calibration dataset. The calibration model was used to predict each case in the validation data set, and then to calculate the mean squared prediction error (MSPE) as follows:

$$\mathrm{MSPE} = \frac{\sum_{i=1}^{n^*}(Y_i - \hat{Y}_i)^2}{n^*}$$

where Y_i is the response variable in the ith validation case, $\hat{Y}_i$ is the predicted value for the ith validation case based on the calibration data set, and n^* is the number of cases in the validation data set.

If the MSPE is fairly close to the mean square error (MSE) based on the calibration model fit to the calibration data set, then the MSE for the selected calibration model is considered good enough with no serious bias to affect the predictive ability of the model (Kutner et al., 2005). To validate the selected calibration models, we also compared the measured ECe values from the Pariette watershed to ECe values predicted by the QR models.

Existing Calibration Model Approaches

Simple and Multiple Linear Regression Models

The simple linear regression (SLR) model utilizes the relation between two variables to predict a random response variable (e.g., ECe) from a single predictor variable (e.g., ECa) (McKenzie et al., 1989). The multiple linear regression (MLR) is similar to the SLR in every respect except that two or more predictor variables are used for making predictions. The appropriateness of the SLR and MLR models for calibrating ECa data (e.g., McKenzie et al., 1989; Corwin and Rhoades, 1982, 1984) depends on non-violation of assumptions such as independence, normality, constancy of error variance, and collinearity (only for MLR).

Spatial Regression Models

Natural logarithm transformations of the response variable (ECe) and the predictor variable (EC_V and EC_H) present a special case of a multiple linear regression model with a spatial component. Lesch et al. (1995) developed this model to bridge the shortcomings of other models that performed well using data from mobilized and automated sensor systems as well as required data from simultaneous measurements of other secondary soil properties. This model relaxes the linear regression model assumption of independence by recognizing the spatial autocorrelation of the conductivity measurements observed in the field. Unlike the geostatistical models requiring large amounts of calibration data (Webster and Oliver, 1992), the spatial regression model requires less data and is easier to estimate (Lesch et al., 1995). The model can be stated as follows:

$$\ln \mathrm{ECe}_i = \beta_0 + \beta_1 \ln \mathrm{EC}_{Hi} + \beta_2 \ln \mathrm{EC}_{Vi} + \beta_3 \mathrm{Easting} + \beta_4 \mathrm{Northing} + \varepsilon_i \quad [1]$$

where EM38 signal readings (EC_H and EC_V) are logarithm transformed and decorrelated into principal component scores, and location coordinates (Easting and Northing) are centered and scaled (ESAP ver.2.35, 2006 available at http://www.ars.usda.gov/Services/docs.htm?docid=8918).

Essentially, this first-order trend surface spatial regression model is a ground-truthing approach in which both dipole modes of the EMI signal readings are decorrelated to eliminate collinearity and used to spatially determine salinity (Rhoades et al., 1999). Lesch et al. (1995) demonstrated that this spatially referenced MLR model (stochastic calibration model), which includes both electrical conductivity and trend surface parameters, is comparable and even superior to a classical geostatistical approach (particularly to cokriging that requires a large number of ground truth samples to accurately model the structure of the data). The ESAP-calibrate software (ESAP ver.2.35) was used to build this model and to estimate the accuracy of the predictions.

A New Calibration Model Approach
Quantile Regression Models

Methodology: The need for a regression method that describes not just the mean, but every other point in a distribution, was emphasized by Mosteller and Tukey (1977). The QR estimation method introduced by Koenker and Bassett (1978) satisfies this need. In its simplest form, the linear conditional QR model function of ECe given ECa can be stated as follows:

$$Q_{\tau}=(\mathrm{ECe} \mid \mathrm{ECa})=\mathrm{ECa}\beta(\tau) \quad [2]$$

where $\tau\in(0,1)$ and $\beta(\tau)$ is the marginal change in the τ^{th} quantile due to the marginal change in the predictor variable (ECa).

Conventional regression methods usually employ minimization of the sum of squared residuals to estimate the conditional mean function (e.g., SLR, MLR models). These OLS models are widely used measures of central location and grand summary statistics because they are easy to calculate without high-powered computing capabilities. In contrast, the QR's objective function minimizes a weighted sum of the absolute deviations to model the conditional quantile functions—a more robust measure of location with estimated coefficient vector that is insensitive to outliers on the dependent variable. Asymmetric weights are used at all quantiles, τ (where $0 < \tau < 1$) but the median ($\tau = 0.5$). The QR minimization problem can be expressed as follows:

$$\min_{\beta}\frac{1}{n}\sum_{i=1}^{n}\rho_{\tau}\left(\mathrm{ECe}-\mathrm{ECa}\beta\right)$$

where $\rho_{\tau}(u)$ is often called the check function (Koenker and Bassett, 1978) and is defined as $\rho_{\tau}(u)=u[\mathrm{t}-I(u<0)]$; I is a binary indicator function, which takes a value of 1 if its argument is true and 0 otherwise, and $\beta = \beta_0,\beta_1,\ldots,\beta_p$.

The complexity of computing the QR's objective function is simplified using a linear programming representation such as the simplex algorithm (Koenker, 2005). A variety of QR analyses can be implemented with software such as R and SAS (SAS Institute, Cary NC). The QR algorithm employs the full data set, and avoids problems associated with sample selection (such as bias of parameter estimates), which are encountered by segmenting the dependent variable into subsets of its unconditional distribution and applying OLS on the subsets (Newsome and Zietz, 1992; Heckman, 1979). Estimates of standard errors and the variance-covariance matrix of the QR coefficients are obtained by a method of Koenker and Bassett (1982) and Rogers (1993). For heteroscedastic error distribution, it is preferable to use a bootstrap resampling procedure for better estimates of standard error (Gould, 1992).

The strength of the QR estimation method is seen in more efficient estimates than those of conventional regression methods especially when the error term is non-normal (Portnoy and Koenker 1989; Koenker and Bassett, 1978). This is due to the robustness of the QR method against outliers in the response variable and the fact that it makes no distributional assumption about the error term in the model as opposed to the conventional least squares regression models where departures from normality, homoscedasticity, and independence, invalidate the model inferences (Borgoni, 2011). In addition to a more robust measure of central location– median quantile, the QR models characterize the scale and shape of the entire conditional distribution of the dependent variable given a set of covariates (Koenker and Machado, 1999). Other convenient features of QR are:

1. It offers equivariant to monotone interpretation of transformed data (Koenker and Machado, 1999). For example, the natural logarithm of the 0.7 conditional quantile of salinity is equivalent to the 0.7 conditional quantile of the natural logarithm of salinity; and
2. The QR estimator $[\beta(\tau)]$ can exhibit more efficient asymptotic behavior, due to the nonlinearity of $\beta(\tau)$ and its non-Gaussian errors, which improves the description of the relation among covariates. This will yield greater insight about data distributions.

Interpretation: Similar to the concept of the percentile height of a baby compared with a regional or national reference for heights of all babies of the same age, in which a child at the 80th percentile in height implies it is taller than 80% of children of that reference age, QR estimates the conditional quantile of the response variable's distribution as a function of observed predictors. Thus, at any specified quantile, τ (where $0 < \tau < 1$), differences in a response variable can be modeled as a change in some observed predictor variables to obtain the estimated conditional τ^{th} quantile surfaces (Koenker and Bassett, 1978). Parameter estimates from the conditional mean models are straightforward to interpret. Linear QR estimates have inherited the same interpretation as those in conventional linear regression models, except that it is defined for specified quantiles. The QR estimates can be interpreted as the rate of change of the response variable conditional on adjusting for the effects of the other variables in the model, defined for some specified quantiles. Such a change that is defined at any specific τ^{th} quantile is not captured by the conventional regressions. Thus, the interpretation of QR's estimates allows the magnitude of disparity existing at various points on the lower and upper tails and the center to be explained.

Prediction and Application: In heterogeneous media such as soils, the effects of covariates on the dependent variable may be different at the center from the tails. This differential impact on the dependent variable's distribution provides additional information about the estimated QR functional relation between the variables, particularly, if the relationship evolves across its conditional distribution. Thus, QR improves predictive ability by describing the full distributional impact. In contrast, the conditional mean models cannot be readily extended to non-central locations that may be of interest in heterogeneous soil property studies. Cade and Noon (2003) pointed out merits of modeling heterogeneous variation in response distributions using QR without the need to specify the variance around a mean effect. Because the conventional regression model assumptions (e.g., constancy of the error term) are rarely met in real life, focusing exclusively on the conditional mean approaches can fail to capture informative trends in the response distribution if it has heavy tails. By modeling every point along the distribution of the dependent variable, a complete picture of the location, scale and shape can be described using QR. In addition, the Scharf et al. (1998) analyses testing the relationship between prey length and predator length for piscivorous fishes showed that QR is an improvement to conventional regression models because QR provides consistent estimates of slope for upper and lower bounds. They argued that such information requiring knowledge of the boundaries of polygonal relationships are important in ecological associations.

Quantile regression is applicable where the conventional least squares regression is less successful, where the relationships between variables are weak (Cade and Noon, 2003), and where there is need to understand the behavior of the entire distribution (Cade and Noon, 2003; Koenker, 2005). Quantile regression is particularly useful where the tails and the central location of the conditional distributions vary at different degrees with the covariates due to heterogeneity in the factors affecting the covariates. In such situations, the change in the conditional quantile depends on the quantile. For instance, the regression coefficients for low salinity soils (say $\tau < 0.05$) would be different from those of medium salinity soils (say $\tau = 0.5$) or high salinity soils (say $\tau > 0.95$) when the relationship between ECe and ECa is modeled.

RESULTS AND DISCUSSIONS

Soil Properties Affecting Electormagnetic Induction Signal Readings

The depth profiles of salinity, clay content, CEC, TOC and TIC from six representative field sites including different soil series are presented (Fig. 3). The soils varied widely in clay content (16–65%), CEC (<1–140 mmol kg^{-1}) and TIC (0.1–5%) at the specified depths. While salinity variation was highest in the subsoil, and is closely related to the amounts of clay and inorganic carbon species at this depth, TOC was, as expected, highest in the topsoil. High CEC at the soil surface corresponds with the high organic matter content, and the decreasing trend of CEC to a depth of 0.9 m is due to the absence of the illuvial accumulation of organic matter below 0.3 m. Illuvial clay between 0.6 and 1.2 m may be responsible for an increase in CEC below 0.9 m (Fig. 3b and 3e vs. Figure 3c). The main point is that these properties differ with depth and among soils, due to the process of horizonation (e.g., the translocation and accumulation of soil components by the action of soil-forming factors; Fig. 3). As a result of inconsistent patterns in the relationships of each soil property with depth, and between two properties across the depth layers for all profiles, the best parameter in the subset of properties affecting the EMI readings for use in calibration was just salinity (ECe) (Appendices: Table A1 and Table A2). Therefore, constructing a direct calibration between EMI signal readings and salinity is inevitable, even though the inclusion of a depth variable as an additional predictor to account for differences in soil properties within the pedons due to the pedogenic processes is reasonable and strategic.

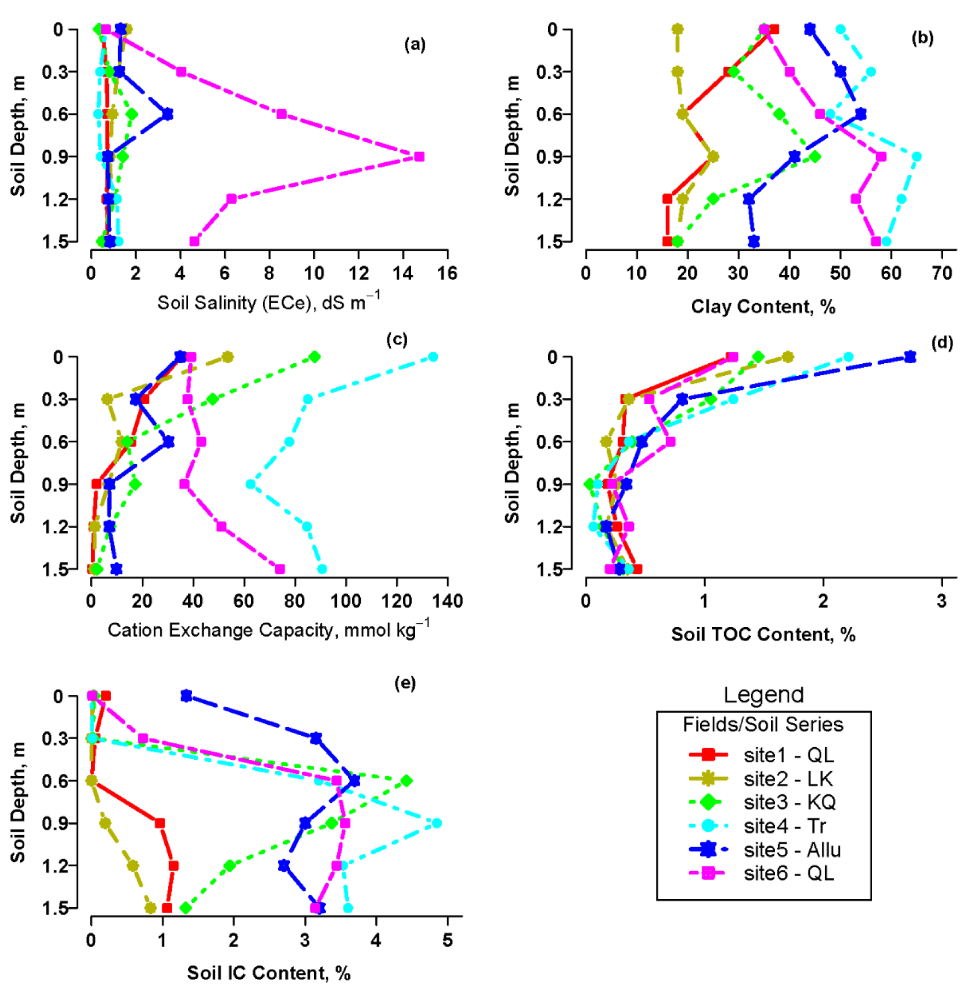

Fig. 3. The depth profiles of selected soil properties [(a) salinity, (b) clay content, (c) cation-exchange capacity, (d) total organic, and (e) inorganic carbon contents] known to directly and indirectly influence the EMI signal readings, from six representative field sites consisting of different soil series (1. Quinney Silt Loam (QL); 2. Lewiston/Kidman Fine Sandy Loam (LK); 3. Kidman Fine Sandy Loam/Quinney Silt Loam (KQ); 4. Trenton Silty Clay Loam (Tr); 5. Mixed Alluvial Land (Allu); 6. Quinney Silt Loam, QL).

Table 2. Simple linear quantile regression (QR) estimates of salinity calibration models of the IMB subbasin in Cache County based on 350 observations. Columns 2 and 8 present the conditional quantile estimates. The *t*-statistic significance level of the parameter estimates are placed next to the estimates and are denoted with asterisks. The R^2 values for the conditional quantiles of the QR are also reported. Statistical significance of estimates at 0.05, 0.001, and 0.0001 are represented with *, **, and *, respectively. (Note that a higher R^2 value influenced the choice of an electromagnetic induction (EMI) dipole orientation used in the models).**

Profile characteristics	Conditional quantiles (τ) of Quantile regression							
	.02	.10	.25	.50	.75	.90	.98	mean
EC_V	0.0030**	0.0045**	0.0112***	0.0351***	0.0558***	0.0716***	0.0797***	0.0423***
intercept	0.1767**	0.2256**	0.1976	−0.2728	−0.3120	−0.0200	2.4709*	-0.3677*
R^2 value	0.027	0.032	0.063	0.182	0.390	0.464	0.506	0.498
EC_{V25}†	0.0112	0.0222***	0.0319***	0.0993***	0.1475***	0.2536***	0.4985*	0.1193***
intercept	0.2034	0.1954*	0.3528***	0.2011	0.5778***	1.1490	1.7019	0.4626**
R^2 value	0.028	0.040	0.057	0.146	0.290	0.307	0.330	0.387
EC_{H25ECe}††	0.1723***	0.1874***	0.2567***	0.3031***	0.3586***	0.4201***	0.4605***	0.3301***
intercept	−0.3869	−0.0730	−0.1908	0.0124	0.1628	0.3481***	0.8330**	−0.0859
R^2 value	0.225	0.326	0.431	0.580	0.700	0.770	0.817	0.870

† Assumes homogeneous profile based on McNeill's apparent electrical conductivity (ECa) depth response curve (McNeill, 1980)

†† developed for non-homogeneous profile.

Existing Regression Models

The SLR and MLR models are rejected because they violate model assumptions of normality and homoscedascity and thus invalidate any inference drawn from such models (Tables 2– 6). The fits of the first-order trend surface spatial regression models (Eq. [1]) are equally weak (R^2 between 0.07 and 0.63 for the five depths) with parameter estimates that are not significantly different from zero (p values > 0.05) (Appendices: Table A3). However, the mean effects are included in Tables 2 through 6, to show that even though the fit could be as high as 0.87, that the predictability of such mean estimates is influenced by meeting model assumptions. Clearly, since none of the existing salinity calibration models perform sufficiently well, there is a need for a more flexible regression framework, such as the QR.

Simple Linear Quantile Regression Models

Results of the QR estimates of the salinity calibration models for the bulk soil profile and by soil depth for the Cache County soils are presented in Tables 2, 3, 4, and 5. Regardless of the EMI signal readings forms (e.g., EC_V, EC_{V25}, EC_{H25ECe}),

Table 3. Simple linear quantile regression (QR) estimates of salinity calibration models of the IMB subbasin in Cache County by depth using the raw bulk EMI signal readings as predictor. Columns 2 and 8 present the conditional quantile estimates. The *t*-statistic significance level of the parameter estimates are placed next to the estimates and are denoted with asterisks. The R^2 values for the conditional quantiles of the QR are also reported. Statistical significance of estimates at 0.05, 0.001, and 0.0001 are represented with *, **, and *, respectively. (Note that a higher R^2 value influenced the choice of an EMI dipole orientation used in the models)**

Raw bulk EC_V or EC_H reading	Conditional quantiles (τ) of quantile regression							
	.02	.10	.25	.50	.75	.90	.98	mean
0-0.3m								
EC_H	0.0032	0.0026	0.0035*	0.0048	0.0154	0.0474	0.1634	0.0225**
Intercept	0.2499***	0.3773***	0.4289***	0.5638***	0.6014	0.8231	1.1316	0.5023
R^2 value	0.039	0.030	0.021	0.015	0.024	0.191	0.324	0.130
0.3–0.6m								
EC_H	0.0073	0.0078*	0.0139	0.0477***	0.0587***	0.0933*	0.0657	0.0460***
intercept	0.1627	0.1973	0.2511	−0.1446	0.3458	0.5009	3.1891	0.2245
R^2 value	0.075	0.068	0.085	0.184	0.363	0.369	0.498	0.441
0.6–0.9m								
EC_V	0.0105	0.0125	0.0179	0.0409***	0.0501***	0.0509*	0.0470**	0.0398***
intercept	−0.1383	0.0141	0.0400	−0.4260	−0.2328	0.4859	1.2984	−0.3064
R^2 value	0.100	0.121	0.179	0.353	0.524	0.650	0.707	0.694
0.9–1.2m								
EC_V	0.0162	0.0197	0.0441* *	0.0536***	0.0744***	0.0927***	0.0842*	0.0663***
Intercept	−0.3505	−0.3545	−1.0043	−0.6592	-0.9076**	−0.8753	1.7711	-1.2707***
R^2 value	0.024	0.134	0.213	0.394	0.581	0.622	0.705	0.749
1.2–1.5m								
EC_V	0.0157	0.0197	0.0408**	0.0503***	0.0748***	0.0759***	0.0592	0.0612***
Intercept	−0.1749	−0.1869	−0.8170	−0.5738	−0.6421	0.1371	3.4202	−0.8207*
R^2 value	0.128	0.176	0.213	0.368	0.542	0.517	0.616	0.704

Table 4 Simple linear quantile regression (QR) estimates of salinity calibration models of the IMB subbasin in Cache County by depth using McNeill's (1980) ECa depth weighted response curve readings as predictor. Columns 2 and 8 present the conditional quantile estimates. The *t*-statistic significance level of the parameter estimates are placed next to the estimates and are denoted with asterisks. The R^2 values for the conditional quantiles of the QR are also reported. Statistical significance of estimates at 0.05, 0.001, and 0.0001 are represented with *, **, and *, respectively. (Note that a higher R^2 value influenced the choice of an EMI dipole orientation used in the models)**

EC_a depth-response curve†	Conditional quantiles (τ) of quantile regression							
	.02	.10	.25	.50	.75	.90	.98	mean
0–0.3m								
EC_{H25}	0.0064*	0.0045	0.0049	0.0143	0.0436	0.0791	0.3418	0.0513***
Intercept	0.2818***	0.3886***	0.4640***	0.5290**	0.5517	0.9507	0.6751	0.4503
R^2 value	0.048	0.028	0.021	0.026	0.054	0.218	0.365	0.186
0.3–0.6m								
EC_{H25}	0.0336	0.0360	0.0751	0.1561***	0.2453***	0.4101*	0.3254	0.1799***
intercept	0.1230	0.1782	0.1430	0.0532	0.3670	0.4835	2.9234	0.3106
R^2 value	0.069	0.067	0.083	0.180	0.344	0.339	0.477	0.439
0.6–0.9m								
EC_{H25}	0.1532	0.2063	0.3318***	0.4664***	0.7171***	0.6964***	0.5678	0.4890***
intercept	0.0029	−0.0631	−0.0689	−0.0842	−0.1135	0.5991	2.1541	0.0136
R^2 value	0.206	0.189	0.241	0.371	0.508	0.633	0.676	0.693
0.9–1.2m								
EC_{V25}	0.1235	0.1763	0.3896**	0.4688***	0.5695***	0.7639***	0.6359*	0.5460***
Intercept	−0.2827	−0.4515	−1.1532	−0.8805*	−0.6978**	−0.8018	1.7980	−1.2387***
R^2 value	0.036	0.136	0.222	0.416	0.607	0.636	0.707	0.781
1.2–1.5m								
EC_{H25}	0.0904	0.0911	0.3118**	0.3458***	0.4503***	0.4166***	0.3769*	0.3853***
Intercept	−0.2144	0.0925	−0.8073	−0.5048	−0.2094	1.2221	3.9896**	−0.4719
R^2 value	0.090	0.133	0.236	0.385	0.539	0.521	0.681	0.718

† Assumes homogeneous profile based on McNeill's apparent electrical conductivity (ECa) depth response curve (McNeill, 1980).

Table 5. Simple linear quantile regression (QR) estimates of salinity calibration models of the Irrigated Middle Bear (IMB) subbasin in Cache County by depth using electromagnetic induction (EMI) reading partitioned with electrical conductivity of the saturation paste extract (ECe) depth profile ratio as predictor. Columns 2 and 8 present the conditional quantile estimates. The *t*-statistic significance level of the parameter estimates are placed next to the estimates and are denoted with asterisks. The R^2 values for the conditional quantiles of the QR are also reported. Statistical significance of estimates at 0.05, 0.001, and 0.0001 are represented with *, **, and *, respectively. (Note that a higher R^2 value influenced the choice of an EMI dipole orientation used in the models)**

ECe depth profile ratio†	Conditional quantiles (τ) of quantile regression							
	.02	.10	.25	.50	.75	.90	.98	mean
0-0.3 m								
EC_{H25ECe}	0.0950	0.2106	0.3099***	0.3006***	0.3210***	0.4385***	0.4367***	0.3380***
Intercept	0.0771	−0.0472	−0.2028	0.0912	0.2124	0.3259	0.9221*	0.0261
R^2 value	0.111	0.257	0.345	0.523	0.635	0.791	0.845	0.903
0.3-0.6 m								
EC_{H25ECe}	0.3441	0.2672**	0.3226***	0.3451***	0.4165***	0.4405***	0.5423***	0.3854***
intercept	−1.2083	−0.4440	-0.4061	−0.1205	0.0201	0.3970*	0.4195	−0.2643*
R^2 value	0.210	0.335	0.455	0.580	0.692	0.738	0.803	0.874
0.6-0.9 m								
EC_{H25ECe}	0.1071	0.1749**	0.2223***	0.2964***	0.3434***	0.4190***	0.4280***	0.3201***
intercept	0.0241	0.0024	−0.0878	−0.0123	0.1623	0.3741	0.6430	−0.0952
R^2 value	0.270	0.309	0.401	0.529	0.649	0.730	0.781	0.826
0.9-1.2 m								
EC_{H25ECe}	0.1781	0.1666***	0.2314***	0.3057***	0.3388***	0.4157***	0.4826***	0.3253***
Intercept	-0.4669	0.0049	−0.1531	−0.0827	0.3227	0.3299	0.7140	−0.1602
R^2 value	0.333	0.380	0.471	0.608	0.731	0.789	0.851	0.875
1.2-1.5 m								
EC_{H25ECe}	0.1743	0.2029***	0.2602***	0.3082***	0.3778***	0.4072***	0.4765***	0.3330***
Intercept	-0.4093	−0.3090	−0.2693	−0.1510	0.0061	0.3536	1.0670	−0.1755
R^2 value	0.328	0.385	0.468	0.598	0.699	0.717	0.798	0.863

† Developed for non-homogeneous profile.

Table 6. Multiple linear quantile regression (QR) estimates of salinity calibration models of the Irrigated Middle Bear (IMB) subbasin in Cache County based on 350 observations. Columns 2 and 8 present the conditional quantile estimates. The *t*-statistic significance level of the parameter estimates are placed next to the estimates and are denoted with asterisks. The R^2 for the conditional quantiles of the QR are also reported. Statistical significance of estimates at 0.05, 0.001, and 0.0001 are represented with *, **, and *, respectively. Mean squared error (MSE) for the calibration data and mean squared prediction error (MSPE) for validating the calibration model with an independent test dataset (N = 42) from an irrigated agricultural field in the Pariette watershed, UT, are also presented. (Note that a higher R^2 value influenced the choice of an EMI dipole orientation used in the models)**

Profile characteristics	Conditional quantiles (τ) of quantile regression							
	.02	.10	.25	.50	.75	.90	.98	mean
EC_H	0.0049**	0.0086***	0.0195***	0.0566***	0.0790***	0.1054***	0.1459***	0.0628***
Depth†	0.0551	0.1794*	0.2549*	0.5141***	0.7283*	0.5199	0.7208	1.2202***
intercept	0.1613	0.1072	0.0315	−0.5411***	−0.5387	0.1142	1.1797	−1.0034***
R^2 value	0.036	0.050	0.089	0.227	0.394	0.478	0.547	0.535
EC_{V25}‡	0.0112*	0.0202***	0.0307***	0.0947***	0.1445***	0.2526***	0.4861*	0.1172***
Depth	−0.0042	0.0428	0.0688	0.3225*	0.5297	0.9697	0.5862	0.2601
intercept	0.2060*	0.1987**	0.3071***	0.0138	0.2407	0.4523	1.5037	0.2955
R^2 value	0.028	0.041	0.058	0.154	0.296	0.315	0.330	0.387
EC_{H25ECe}§	0.1701***	0.2009***	0.2626***	0.3082***	0.3674***	0.4194***	0.4630***	0.3334***
Depth	−0.0830	−0.2063	−0.1839*	−0.1820	−0.1342	−0.1174	0.2848	−0.2287
intercept	−0.2699	0.0198	−0.0749	0.0920	0.2087	0.4521***	0.7088*	0.0641
R^2 value	0.226	0.338	0.437	0.583	0.701	0.770	0.819	0.871
MSE	3.9881	2.6407	1.4745	0.9229	1.1412	2.3744	5.4875	0.8869
MSPE	3.8178	2.7066	1.8955	2.1379	3.6439	6.6271	12.2714	2.3629

† depth is the midpoints of the 0.3 m interval soil layers (i.e., 0.15, 0.45, 0.75, 1.05, 1.35m)

‡ assumes homogeneous profile based on McNeill's ECa depth response curve (McNeill, 1980)

§ developed for non-homogeneous profile

used as explanatory variables to estimate salinity, the QR estimates reveal the percentile of the distribution that is described by least squares regression. In this case, the mean estimates were higher than the median quantile (τ = 0.50) estimates. This finding is reasonable in regions dominated by low salinity calcareous soils, where a few locations with high salinity soils would skew the mean upward and away from the median, resulting in the overestimation of salinity for most of the soils (with low ranged salinity). The importance of EMI signal readings in predicting mean soil salinity has already been established by previous salinity calibration models. What is more important, however, is to know whether the predictive influence of the EMI signal reading for soil salinity (ECe) is the same for soils with low, average, and high salinities. Results from QR modeling seek to answer such a question, and thus provide a broader basis for understanding the relationship between EMI signals and soil salinity. From Table 2, it is clear that a change in a specified quantile (τ = 0.02, 0.10, 0.25, 0.50, 0.75, 0.90, or 0.98) of soil salinity (ECe), produced by a unit change in the EMI signal reading, is significantly different across quantiles (the QR coefficients increased with increase in the τ values). This ability to describe every point of the distribution proves the necessity of the QR approach for analyzing such heterogeneous data. Similar results are found in Table 6.

Increases in the QR coefficients across the seven estimated quantiles, and observed for all three EMI input forms, indicate the nonexistence of location shift effects. The QR parameter estimates have several slopes that vary significantly from each other across the distribution (p-value < 0.0001). The slopes increase with increasing quantiles and also with soil depths to 0.6 m, decrease for soil depths between 0.6 and 0.9 m, and then increasing again at soil depths below 0.9 m for each specified quantile (Table 5). This observation can be explained by the presence of a few extremely high salinity locations in these low to moderately saline calcareous soils, and to accumulated salinity at depth due to the incomplete leaching of salts by irrigation waters (Fig. 3a). The slope effects at the various specified quantiles for the three EMI signal reading forms are shown (Fig. 4). Slopes for the higher quantiles are substantially different from the ones for the lower quantiles. Thus, the different effects of EMI signal readings at different quantiles of the distribution confirm the large amount of heterogeneity in the salinity calibration models, and substantiate the use of a more comprehensive technique like QR, which is capable of addressing the variability within the distribution.

Multiple Linear Quantile Regression Models

Results obtained by including soil depth as an additional predictor term to the EMI signal readings in multiple linear QR models to estimate soil salinity are presented in Table 6. When the fits of these multiple linear QR models, for each of the specified conditional quantiles, are compared with corresponding simple linear QR models (Table 6 vs. Table 2), "Depth" plays a significant role only in predicting median salinity (p-value = 0.0146) for models with EC_{V25} readings, and in predicting the first decile (τ = 0.1, p-value = 0.0361) and lower quartile

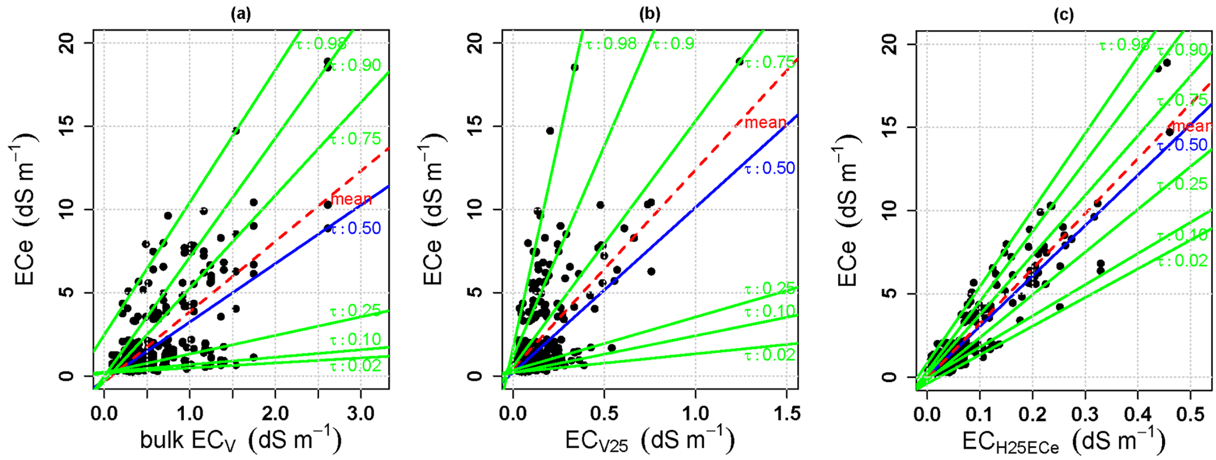

Fig. 4. Plots of predicted conditional quantiles of electrical conductivity of the saturation paste extract (ECe) at 7 specified quantiles (τ = 0.02, 0.1, 0.25, 0.5, 0.75, 0.9, 0.98) and the conditional mean model of ECe against a) the raw bulk electromagnetic induction (EMI) readings (EC_V), b) depth weighted EMI response for homogeneous profiles (EC_{V25}), and c) the depth weighted EMI response based on observed ECe profile ratios for heterogeneous profiles (EC_{H25ECe}) in the IMB subbasin of Cache County, Utah (*N* = 350).

salinity ($\tau = 0.25$, p-value < 0.0004) for models with EC_{H25ECe} readings. The p-values of the conditional QR estimates indicate that "Depth" can improve estimates of salinity within the median and lower quartile distribution for models with EC_{V25} and EC_{H25ECe} predictors, respectively. We expected "Depth" to play a significant role in predicting the soil profile salinity given the processes that move salts up and down the profile at different times of the year and under different management practices. Such processes are responsible for high salinity at the soil surface in response to evapo-concentration gradients created by higher temperatures and lower humidity in the ambient air than soil, and also for high salinity in the subsoil after leaching and mobilizing the salts with irrigation waters or spring melt waters.

We also observed that the results of the Wald test (based on chi-square distribution), used to determine the significance of the regression parameter estimates, are similar to those of the t-statistic (denoted with stars) (Tables 2–6). This observation agrees with the proof of convergence of the distribution of the test statistic to chi-square under the null hypothesis as reported by Koenker and Machado (1999).

Quantile Regression Estimated Parameters with Confidence Limits for Salinity

The quantile plots for the intercept and predictor variables (EC_{H25ECe} and Depth) are presented (Fig. 5a, b, and c). In Fig. 5b, for example, the regression coefficient at a given quantile indicates the effect of a unit change in the EC_{H25ECe} signal reading on soil salinity, after accounting for the effects of depth, with 95% confidence interval bands. Similar to the interpretation of Koenker and Hallock (2001) for the QR parameters, the intercept is the estimated conditional quantile function of the soil salinity distribution of a soil collected from Cache Valley at no defined soil depth of sampling and no EMI signal readings. These interpretations are similar to those of conventional linear

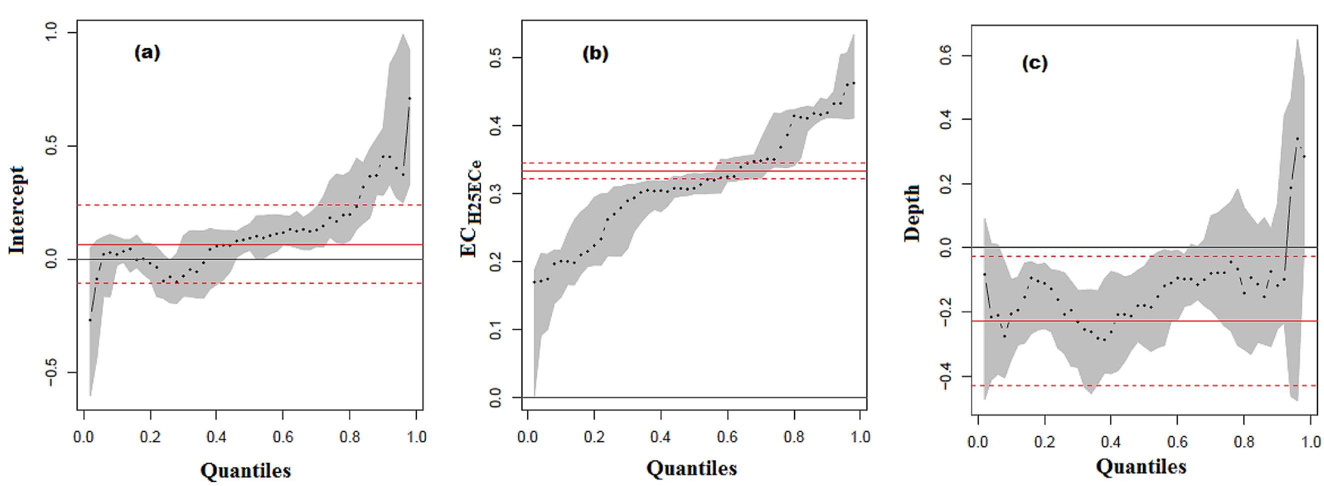

Fig. 5. Parameter estimate plots from a multiple quantile regression (QR) for the conditional quantiles of electrical conductivity of the saturation paste extract (ECe) against the horizontal apparent electrical conductivity that is depth-weighted based on teh ECe profile ratios and corrected to the reference temperature 25°C (EC_{H25ECe}) and Depth. For each of the QR coefficients– (a) intercept, (b) EC_{H25ECe} and (c) Depth, the black dotted points with filled solid lines represents the estimated quantiles, $\tau \in (0,1)$. The shaded grey area depicts a 95% pointwise confidence band. A red solid line represents the least squares estimates of the mean effect, with two red dashed lines representing a 95% confidence interval for this coefficient.

regression estimates, except that the QR parameters are defined for specified quantiles.

The quantile plots illustrate how variable the explanatory effects can be. They also highlight that the mean effect is not the optimal way to model the salinity calibration. For instance, the QR estimates (intercept, EC_{H25ECe}, Depth) for ECe lie outside the confidence interval of the mean, indicating that the location shift interpretation of the effects of EC_{H25ECe} and Depth are questionable. A formal test (Khmaladze test) that was conducted to clear doubts about the possible absence of a location shift effect confirmed that neither the individual slope parameters, nor all the slope parameters of the model, jointly satisfied the null hypothesis that the linear model specification is of a location shift or location-scale shift form. The "Depth" parameter came close to exhibiting a location shift effect for most parts of the distribution from a τ of 0.02 to near 0.92, but deviated above 0.92 (Fig. 5c). This can be seen in Fig. 5c as an underestimation of the mean "Depth" effect at most of the specified conditional quantiles.

The QR estimates of the conditional quantile effect of EC_{H25ECe} on ECe show a much larger variation in the lower quantiles (e.g., τ = 0.02, 0.003– 0.187 dS m^{-1}) and upper quantiles (e.g., τ = 0.98, 0.41– 0.54 dS m^{-1}) of the distribution compared to the median (0.33 dS m^{-1}) or the mean (0.32– 0.35 dS m^{-1}). Figure 5b shows that these larger variations on the tails of the distribution manifested as underestimation of EC_{H25ECe} at quantiles $\geq$ 0.75 and overestimation at quantiles $\leq$ 0.50. These plots reiterate the strength of the QR technique in capturing the complete set of the highly variable conditional quantiles and their 95% pointwise confidence band of the parameter estimates.

Review of the multiple QR parameters calculated using Eq. [1] reveals that the parameter estimates for EC_H', Easting, and Northing are not significant (p-value > 0.05) (Appendices: Table A3). Furthermore, the fits of the QR models for the upper two depths at each of the specified quantiles are poor (R^2 values < 0.44) (Appendices: Table A3). Thus, these models are not recommended.

Model Goodness-of-Fit

Results show that on the basis of the R^2 statistic, the fits for the calibration models with the EMI signal readings that account for heterogeneity in soil profile salinity (EC_{H25ECe}), perform better than models with EMI readings that assume profile homogeneity (EC_{V25}), or those using the direct raw EMI readings (EC_V or EC_H; Table 2 and Table 6). Similar results are found when the R^2 values are compared with those of the corresponding soil depths (Table 5 vs. Tables 3 and 4). The R^2 values of QR models increase with increasing τ (Table 2–6). The observed high R^2 at higher quantiles is indicative of a highly skewed and heavy upper tailed conditional distribution resulting from substantial differences between the conditional and unconditional estimates. It also suggests a higher quality fit, and the stronger significance of the explanatory variables, at higher than lower quantiles.

Model Validation

Table 6 presents the MSE and MSPE based on a calibration and independent validation data set, respectively, for specific conditional quantiles of the multiple QR models with EC_{H25ECe} and Depth as predictors. The results show that the MSPE values are fairly close to the MSE and not seriously biased for conditional quantile models with $\tau \leq 0.25$. But as τ increases to higher quantiles, the MSPE increases faster than the MSE and their difference widens. In this circumstance, we have to rely on the MSPE as an indicator of how well these conditional quantile models at higher quantiles ($\tau > 0.25$) will predict in the future (Kutner et al., 2005). Nonetheless, the regression model developed from the calibration data of the IMB subbasin is applicable for the irrigated agricultural field of the Pariette watershed with low salinity levels ($\tau \leq 0.25$, ECe < 13.5 dS m^{-1}, N = 42). For the conditional quantile models with $\tau > 0.25$, the MSE of the model calibration dataset underestimates the inherent variability in making future predictions. The appropriateness of the predictive ability of these multiple QR models with $\tau \leq 0.25$ may have been an indication that the new data have ECe within the range of the calibration data, or may simply be indicative of strong support for the applicability of these models under broader circumstances. Results of comparing the measured ECe values from the Pariette watershed to the predicted values based on the conditional QR models depicts a similar finding as explained using the MSE–MSPE statistics (Fig. 6). Again, it is clear that there is less bias between the measured and the predicted ECe values for QR models at lower quantiles ($\tau \leq 0.25$) than higher. Although this independent validation requires the calculation of new weighting ratios for the validation dataset, its merits, which include (i) capturing the field-specific inherent heterogeneity of ECe and translating the heterogeneity in ECe to the depth weighted EMI data, and (ii) retaining the predictive ability of the calibration model despite differences in the type and nature of the salts responsible for the salinity at these sites (calibration vs. validation fields), far outweigh the effort in obtaining a few additional

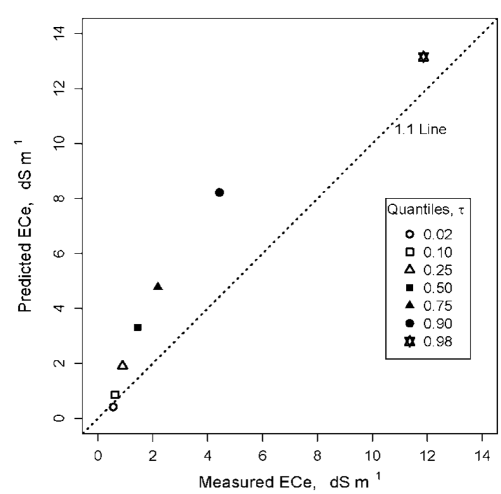

Fig. 6. Measured against predicted electrical conductivity of the saturation paste extract (ECe) values of validation samples (N = 42) from the Pariette watershed (Uinta Basin, UT) based on the conditional quantile regression (QR) models.

validating ground-truth ECe values. These independent validation results support the suitability of the conditional QR models with lower quantiles despite the lower R^2 values of these models.

CONCLUSIONS

Despite the non-homogeneity of potentially perturbing factors affecting ECa, we developed calibration models for predicting salinity directly from EMI signal readings using a QR modeling technique. The QR models capture the variability at different specified conditional quantiles of the salinity distribution. Independent validation of the selected multiple QR models indicates that at low salinity ranges corresponding to conditional quantiles $\tau \leq 0.25$, the conditional quantile models ($Q_{\tau \leq .25}$ = ECe | EC_{H25ECe} + Depth) are applicable to data from low range salinity fields in addition to those of the calcareous soils on which the models are based. Although the R^2 values of these fitted QR models ($\tau \leq 0.25$) are low, the appropriateness of their predictive capability assures their use for prediction at low salinity ranges. The robustness of this novel QR approach (i.e., no requirements for compliance with distributional assumptions, and the ability to describe every point of the dependent variable's distribution) supports its application over the conventional least squares regression method where violations of model assumptions invalidate the statistical inference procedures. The precision with which the heavy upper tail of the salinity distribution is described demonstrates the strength of the QR model and exposes how misleading mean effects can be.

Given the improved performance of the salinity models with EMI signal predictors that account for non-homogeneity in the profile, we encourage future attempts at EMI depth-weighting to adopt this new weighting procedure rather than continuing to use models that assume homogeneity, which is rarely observed in the real world. Although it requires a few ground-truth ECe data values to calculate the ECe profile ratios, this newly proposed depth-weighting procedure removes the complexity of modeling different equations for regular, inverted, and uniform salinity profiles (Corwin and Rhoades, 1984; Rhoades, 1992). Finally, we recommend that future conditional mean regression models be complemented with QR techniques to provide a broader understanding of the entire conditional distribution.

ACKNOWLEDGEMENT

This research was supported by the Utah Agriculture Experiment Station, Utah State University, and approved as journal paper number 8466. We are also thankful to the Utah Drought Initiative Project of the Bear River Basin Authority for their funding. We thank teh associate editor and three anonymous reviewers for their help with improving teh quality of our article. Our sincere appreciation also goes to Austin Hawks for assistance with sample collection.

APPENDICES

Table A1. Comparison of reduced multiple linear regression (MLR) models with apparent electrical conductivity (ECa) + Depth as predictor variables to fuller nested models with Clay and saturation percentage (SP). (Note: Cation-exchange capacity [CEC] and total organic C [TOC] variables were only available for surface modeling). The adjusted R^2 values and predictor variables that were not significant in the models are presented. The P values (fourth column) compare each of the fuller models with the reduced model at significance level of 0.05.

Predictor variables	Adj. R^2	Non-significant coefficients†	Model comparison‡
EC_H + Depth	0.535	—	
EC_H + Depth + Clay	0.534	Clay	P=0.529
EC_H + Depth + SP	0.534	SP	P=0.663
EC_H + Depth + Clay + SP	0.533	Clay and SP	P=0.816
EC_{V25} + Depth	0.387	Depth	
EC_{V25} + Depth + Clay	0.396	Depth	P=0.012
EC_{V25} + Depth + SP	0.392	Depth and SP	P=0.063
EC_{V25} + Depth + Clay + SP	0.395	Depth, Clay, and SP	P=0.042
EC_{H25ECe} + Depth	0.871	Depth	
EC_{H25ECe} + Depth + Clay	0.874	Depth	P=0.003
EC_{H25ECe} + Depth + SP	0.874	—	P=0.002
EC_{H25ECe} + Depth + Clay + SP	0.874	Clay and SP	P=0.006
Log transformed ECe models§	**Adj. R^2**	**Non-significant coefficients†**	**Model comparison‡**
EC_H + Depth	0.443	—	
EC_H + Depth + Clay	0.441	Clay	P=0.992
EC_H + Depth + SP	0.443	SP	P=0.380
EC_H + Depth + Clay + SP	0.443	Clay and SP	P=0.361
EC_{V25} + Depth	0.291	-	
EC_{V25} + Depth + Clay	0.295	Depth and Clay	P=0.071
EC_{V25} + Depth + SP	0.299	-	P=0.019
EC_{V25} + Depth + Clay + SP	0.298	Clay and SP	P=0.064
EC_{H25ECe} + Depth	0.698	Depth	
EC_{H25ECe} + Depth + Clay	0.702	Depth	P=0.020
EC_{H25ECe} + Depth + SP	0.698	Depth and SP	P=0.326
EC_{H25ECe} + Depth + Clay + SP	0.703	Depth and SP	P= 0.026
For surface depth (70 samples)¶	**Adj. R^2**	**Non-significant. coefficients†**	**Subset comparison#**
EC_H + SP + Clay + CEC + TOC	0.150	SP, Clay, CEC, and TOC	
EC_H + SP + TOC	0.159	TOC	P=0.534
EC_{V25} + SP + Clay + CEC + TOC	0.170	SP, Clay, CEC, and TOC	
EC_{V25} + SP + TOC	0.177	TOC	P=0.495
EC_{H25ECe} + SP + Clay + CEC + TOC	0.900	SP, Clay, CEC, and TOC	
EC_{H25ECe} + Clay	0.905	Clay	P=0.978

† Coefficients that are not significant at 0.05 level of significance.
‡ Comparison models with Depth as an additional predictor and nested models with Clay and SP.
§ Predictor variables from a log-normal transformed model.
¶ Predictor variables for surface ECe model with additional variables (CEC and TOC).
# Surface model comparison between full model and 'best' subset model.

Table A2. Comparison of reduced quantile regression (QR) models with apparent electrical conductivity (ECa) + Depth as predictor variables to fuller nested models with Clay and saturated percentage (SP) at specified conditional quantiles. The *P* values (bottom row) compare the reduced model (i.e., EC_{H25ECe} + Depth) with each of the fuller nested models at significance level of 0.05.

Predictor variables	Adjusted R^2 for QR models at specified conditional quantiles (τ)						
	τ = .02	τ = .10	τ = .25	τ = .50	τ = .75	τ = .90	τ = .98
EC_H + Depth	0.036	0.050	0.089	0.227	0.394	0.478	0.547
EC_H + Depth + Clay	0.044	0.051	0.092	0.227	0.394	0.478	0.549
EC_H + Depth + SP	0.036	0.050	0.089	0.227	0.395	0.478	0.551
EC_H + Depth + Clay + SP	0.052	0.057	0.096	0.229	0.396	0.478	0.551
EC_{V25} + Depth	0.028	0.041	0.058	0.154	0.296	0.315	0.330
EC_{V25} + Depth + Clay	0.038	0.046	0.058	0.154	0.303	0.337	0.397
EC_{V25} + Depth + SP	0.033	0.041	0.059	0.155	0.302	0.332	0.348
EC_{V25} + Depth + Clay + SP	0.043	0.049	0.060	0.155	0.303	0.337	0.427
EC_{H25ECe} + Depth	0.226	0.338	0.437	0.583	0.701	0.770	0.819
EC_{H25ECe} + Depth + Clay	0.271	0.389	0.465	0.592	0.708	0.770	0.819
EC_{H25ECe} + Depth + SP	0.243	0.386	0.463	0.590	0.709	0.769	0.819
EC_{H25ECe} + Depth + Clay + SP	0.276	0.393	0.467	0.592	0.710	0.771	0.820
p-values†	< .001	< .001	< .001	0.003	< .001	0.295	0.480

† *p*-values from the comparison between EC_{H25ECe} + Depth model and other nested models with Clay and SP.

Table A3. Multiple quantile regression estimates of salinity calibration models of the Irrigated Middle Bear (IMB) subbasin in Cache County by depth using the raw bulk electromagnetic induction (EMI) signal readings (ECV′ and ECH′- logarithm transformed and decorrelated) and location coordinates of the trend surface (Easting′ and Northing′- centered and scaled) as predictor. Columns 2 to 8 present their conditional quantile estimates. Column 9 reports the mean effect estimated by least squares regression. The *t*-statistic significance level of the parameter estimates are placed next to the estimates and are denoted with asterisks. The R^2 values for conditional quantiles of the QR are also reported. Statistical significance of estimates at 0.05, 0.001, and 0.0001 are represented with *, **, and *, respectively.**

Depth characteristics	Conditional quantiles (τ) of quantile regression							mean
	.02	.10	.25	.50	.75	.90	.98	
0–0.3m								
EC_V'	0.0081	0.0795	0.0974	−0.0074	0.1214	0.3376	0.3949	0.1419
EC_H'	0.0456	−0.0827	−0.1423	−0.0282	−0.0695	−0.4059	−0.5248	−0.1308
Easting′	1.7821	1.1309	0.7359	1.2199	2.0171*	2.6289	1.9677	0.9324
Northing′	-0.5009	−0.4188	−0.3204	−0.5921	−0.0194	0.9779	1.0049	0.1355
intercept	-1.1444	-0.8416***	-0.6932***	−0.3888*	−0.4761*	−0.3364	−0.0307	−0.5269**
R^2 value	0.221	0.146	0.102	0.068	0.086	0.235	0.436	0.071
0.3–0.6m								
EC_V'	0.4367	0.3774*	0.4147**	0.3946**	0.4846***	0.4757*	0.2344	0.4289***
EC_H'	0.0021	−0.0859	−0.1913	−0.0344	−0.0236	−0.0807	−0.0916	−0.0657
Easting′	-0.7807	−1.1410	−0.6938	0.9760	0.4963	−2.0360	−0.4432	0.1908
Northing′	0.8797	0.7822	0.5375	−0.1247	−0.2420	0.4579	−0.5392	0.0250
intercept	-1.2172	-0.8992***	−0.6397*	−0.1399	0.6060	1.4402*	1.8982	0.0423
R^2 value	0.233	0.183	0.150	0.172	0.267	0.177	0.250	0.259
0.6–0.9m								
EC_V'	0.7645	0.5682**	0.6345***	0.5980***	0.5218***	0.4263***	0.4629	0.5616***
EC_H'	-0.2303	−0.1771	−0.2388	−0.0753	−0.0635	0.0967	0.1083	−0.0752
Easting′	0.8106	0.1230	0.2950	0.4920	−0.4897	−0.5496	−1.7876	0.2865
Northing′	0.4623	0.7778	0.8137*	0.3832	−0.1348	0.1510	0.8320	0.3968
intercept	-1.4638	−0.9078**	−0.7466*	−0.0773	0.8917**	1.1070***	1.3073	−0.0411
R^2 value	0.350	0.314	0.287	0.337	0.383	0.438	0.499	0.499
0.9–1.2m								
EC_V'	0.6960	0.5018*	0.7065***	0.7097***	0.6516***	0.4373**	0.4284	0.6555***
EC_H'	-0.1384	−0.0444	−0.0600	−0.0087	0.0998	0.0269	−0.1118	0.0114
Easting′	-0.9328	0.8892	0.3843	−0.5584	−1.0676	−0.1309	0.2117	−0.2886
Northing′	1.3996	0.4647	0.2734	0.5311	0.3542	−0.7094	−0.8944	0.2857
Intercept	-1.3201	−0.8229*	−0.1026	0.2555	0.9239**	1.7021**	1.7887	0.3346*
R^2 value	0.279	0.293	0.372	0.457	0.522	0.463	0.545	0.627
1.2–1.5m								
EC_V'	0.6678	0.5785**	0.6916***	0.6571***	0.4760***	0.3198	0.2974	0.5706***
EC_H'	0.2720	0.1446	0.0008	0.0336	0.2502	0.3999	0.4961	0.1648*
Easting′	-0.5730	−0.2566	−0.3202	1.1731	0.8329	0.3927	−0.8548	−0.0819
Northing′	0.4083	0.2107	0.3728	0.0247	−0.1775	−0.6307	−0.0249	0.2737
intercept	-0.5283	−0.3568	−0.1295	0.0680	0.8357**	1.7869***	2.0164	0.3679
R^2 value	0.355	0.351	0.347	0.375	0.425	0.309	0.344	0.537

REFERENCE

Abdu, H., D.A. Robinson, and S.B. Jones. 2007. Comparing bulk soil electrical conductivity determination using the DUALEM-1S and EM38-DD electromagnetic induction instruments. Soil Sci. Soc. Am. J. 71:189–196.

Borgoni, R. 2011. A quantile regression approach to evaluate factors influencing residential indoor radon concentration. Environ. Model. Assess. 16:239–250. doi:10.1007/s10666-011-9249-3

Burgette, L.F., and J.P. Reiter. 2012. Modeling adverse birth outcomes via confirmatory factor Quantile Regression. Biometrics 68:92–100. doi:10.1111/j.1541-0420.2011.01639.x

Cade, B.S. 2011. Estimating equivalence with quantile regression. Ecol. Appl. 21:281–289. doi:10.1890/09-2060.1

Cade, B., and B. Noon. 2003. A gentle introduction to quantile regression for Ecologists. Front. Ecol. Environ 1:412–420. doi:10.1890/1540-9295(2003)001[0412:AGITQR]2.0.CO;2

Canay, I.A. 2011. A simple approach to quantile regression for panel data. Econometrics J. 14:368–386. doi:10.1111/j.1368-423X.2011.00349.x

Chen, C. 2005. Growth charts of body mass index (BMI) with quantile regression. Proc. Intl. Conf. Algor. Math. Comput. Sci. June 20–23, 2005, Las Vegas, Nevada.

Corwin, D.L., and J.D. Rhoades. 1982. An improved technique for determining soil electrical conductivity—Depth relations from above-ground electromagnetic measurements. Soil Sci. Soc. Am. J. 46:517–520. doi:10.2136/sssaj1982.03615995004600030014x

Corwin, D.L., and J.D. Rhoades. 1984. Measurement of inverted electrical conductivity profiles using electromagnetic induction. Soil Sci. Soc. Am. J. 48:288–291. doi:10.2136/sssaj1984.03615995004800020011x

Corwin, D.L., and S.M. Lesch. 2005. Characterizing soil spatial variability with apparent soil electrical conductivity I. Survey protocols. Comput. Electron. Agric. 46:103–133. doi:10.1016/j.compag.2004.11.002

Francke, T., J.A. Lopez-Tarazon, and B. Schroder. 2008. Estimation of suspended sediment concentration and yield using linear models, random forests and quantile regression forests. Hydrol. Processes 22:4892–4904. doi:10.1002/hyp.7110

Gee, G.W., and J.W. Bauder. 1986. Particle-size Analysis. In: A.L. Page, editor, Methods of soil analysis. Part 1. 2nd ed. Agron. Monogr. No. 9, ASA, Madison, WI. p. 383–411.

Gould, W.W. 1992. Quantile regression with bootstrapped standard errors. Stata Tech. Bull. 9:19–21.

Haddad, K., and A. Rahman. 2011. Selection of the best fit flood frequency distribution and parameter estimation procedure: A case study for Tasmania in Australia. Stochastic Environ. Res. Risk Assess. 25:415–428. doi:10.1007/s00477-010-0412-1

Harvey, O.R., and C.L.S. Morgan. 2009. Predicting regional-scale soil variability using a single calibrated apparent soil electrical conductivity model. Soil Sci. Soc. Am. J. 73:164–169. doi:10.2136/sssaj2008.0074

Heckman, J.J. 1979. Sample selection bias as a specification error. Econometrica 47:153–161. doi:10.2307/1912352

Johnston, M.A., M.J. Savage, J.H. Moolman, and H.M. du Plessis. 1996. Calibration models for interpretation of soil salinity measurements using an electromagnetic induction technique. S. Afr. J. Plant Soil. 13:110–114.

Johnston, M.A., M.J. Savage, J.H. Moolman, and H.M. du Plessis. 1997. Evaluation of calibration methods for interpreting of soil salinity from electromagnetic induction measurements. Soil Sci. Soc. Am. J. 61:1627–1633. doi:10.2136/sssaj1997.03615995006100060013x

Kerry, R., and M.A. Oliver. 2007. Comparing sampling needs for variograms of soil properties computed by the method of moments and residual maximum likelihood. Geoderma 140:383–396. doi:10.1016/j.geoderma.2007.04.019

Koenker, R. 2005. Quantile regression. Cambridge Univ. Press, New York.

Koenker, R. 2012. quantreg: Quantile Regression. R package version 4.79. Available online: http://cran.r-project.org/web/packages/quantreg/index.html. [verified 3/13/2013]

Koenker, R., and G. Bassett, Jr. 1978. Regression quantiles. Econometrica 46:33–50. doi:10.2307/1913643

Koenker, R., and G. Bassett, Jr. 1982. Robust tests for heteroscedasticity based on regression quantiles. Econometrica 50:43–61. doi:10.2307/1912528

Koenker, R., and J.A.F. Machado. 1999. Goodness of fit and related inference processes for quantile regression. J. Am. Stat. Assoc. 94:1296–1310. doi:10.1080/01621459.1999.10473882

Koenker, R., and K. Hallock. 2001. Quantile regression. J. Econ. Perspect. 15:143–156. doi:10.1257/jep.15.4.143

Kutner, H.M., C.J. Nachtsheim, J. Neter, and W. Li. 2005. Applied linear statistical models. 5th ed. McGraw-Hill, Irwin, New York.

Lesch, S.M., D.J. Strauss, and J.D. Rhoades. 1995. Spatial prediction of soil salinity using electromagnetic induction techniques 1. Statistical prediction models: A comparison of multiple linear regression and cokriging. Water Resour. Res. 31:373–386. doi:10.1029/94WR02179

Logan, J.A.R., S.A. Petrill, S.A. Hart, C. Schatschneider, L.A. Thompson, K. Deater-Deckard, L.S. DeThorne, and C. Bartlett. 2012. Heritability across the distribution: An application of quantile regression. Behav. Genet. 42:256–267. doi:10.1007/s10519-011-9497-7

McKenzie, R.C., W. Chomistek, and N.F. Clark. 1989. Conversion of electromagnetic inductance readings to saturated paste extract values in soils for different temperature, texture and moisture conditions. Can. J. Soil Sci. 69:25–32. doi:10.4141/cjss89-003

McNeill, J.D. 1980. Electrical conductivity of soils and rocks. Tech. Note TN– 5. Geonics Ltd., Mississauga ON.

Mosteller, F., and J.W. Tukey. 1977. Data analysis and regression. Addison Wesley, New York.

Newsome, B., and J. Zietz. 1992. Adjusting Comparable Sales Using MRA- The Need for Segmentation. Appraisal J. 60:129–135.

Nogués, J., D.A. Robinson, and J. Herrero. 2006. Incorporating electromagnetic induction methods into regional soil salinity survey of irrigation districts. Soil Sci. Soc. Am. J. 70:2075–2085. doi:10.2136/sssaj2005.0405

Pires, P., J.P. Pereira, and L.F. Martins. 2010. The complete picture of credit default swap spreads—A quantile regression approach. Available at SSRN: Http://ssrn.com/abstract = 1125265 accessed [05/11/2012].

Portnoy, S., and R. Koenker. 1989. Adaptive L-estimation for linear models. Ann. Stat. 17:362–381. doi:10.1214/aos/1176347022

R Development Core Team. 2012. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. Available at: http://www.R-project.org/.

Rhoades, J.D. 1992. Instrumental field methods of salinity appraisal. In: G.C. Topp et al. editors, Advances in measurement of soil physical properties: Bringing theory into practice. SSSA Spec. Publ. 30. ASA, CSSA and SSSA, Madison, WI. p. 231–248.

Rhoades, J.D. 1996. Salinity: Electrical conductivity and total dissolved salts. In: Methods of soil analysis, Part 3., SSSA Book Series No. 5, SSSA, Madison, Wisconsin, p. 417–435.

Rhoades, J. D., F. Chanduvi and S. Lesch. 1999. Soil salinity assessment—Methods and interpretation of electrical conductivity measurements. FAO irrig. Drain. pap. 57. FAO, Rome.

Rhoades, J.D., and D.L. Corwin. 1981. Determining soil electrical conductivity—Depth relations using an inductive electromagnetic soil conductivity meter. Soil Sci. Soc. Am. J. 45:255–260. doi:10.2136/sssaj1981.03615995004500020006x

Robinson, D.A., I. Lebron, S.M. Lesch, and P. Shouse. 2004. Minimizing drift in electrical conductivity measurements in high temperature environments using the EM-38. Soil Sci. Soc. Am. J. 68: 339–345.

Rogers, W.H. 1993. Calculation of quantile regression standard errors. Stata Tech. Bull. 13:18–19.

Scharf, F.S., F. Juanes, and M. Sutherland. 1998. Inferring ecological relationships from the edges of scatter diagrams: Comparison of regression techniques. Ecology 79:448–460. doi:10.1890/0012-9658(1998)079[0448:IERFTE]2.0.CO;2

Slavich, P.G. 1990. Determining ECa—Depth profiles from electromagnetic induction measurements. Aust. J. Soil Res. 28:443–452. doi:10.1071/SR9900443

Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture. 2004. Soil Survey Geographic (SSURGO) Database for Cache County, Utah. Available online at http://soildatamart.nrcs.usda.gov accessed [01/29/2010].

Sudduth, K.A., S.T. Drummond, and N.R. Kitchen. 2001. Accuracy issues in electromagnetic induction sensing of soil electrical conductivity for precision agriculture. Comput. Electron. Agric. 31: 239–264

Sumner, M.E., and W.P. Miller. 1996. Cation exchange capacity and exchange coefficients. In: D.L. Sparks, editor, Methods of soil analysis. Part 3. SSSA, Book series no. 5.SSSA, Madison, WI.

Triantafilis, J., G.M. Laslett, and A.B. McBratney. 2000. Calibrating an electromagnetic induction instrument to measure salinity in soil under irrigated cotton. Soil Sci. Soc. Am. J. 64:1009–1017. doi:10.2136/sssaj2000.6431009x

U.S. Salinity Laboratory Staff. 1954. Diagnoses and improvement of saline and alkali soils. USDA Agric. Handb. 60. U.S. Gov. Print. Office, Washington, DC.

Webster, R., and M.A. Oliver. 1992. Sample adequately to estimate variograms of soil properties. J. Soil Sci. 42:177–192.

Wei, Y., and X. He. 2006. Conditional growth charts (with discussions). Ann. Stat. 34:2069–2031. doi:10.1214/009053606000000623

Wittler, J.M., G.E. Cardon, T.K. Gates, C.A. Cooper, and P.L. Sutherland. 2006. Calibration of electromagnetic induction for regional assessment of soil water salinity in an irrigated valley. J. Irrig. Drain. Eng. 132:436–444. doi:10.1061/(ASCE)0733-9437(2006)132:5(436)

Wollenhaupt, N.C., J.L. Richardson, J.E. Foss, and E.C. Doll. 1986. A rapid method for estimating weighted soil salinity from apparent soil electrical conductivity measured with an above ground electromagnetic induction meter. Can. J. Soil Sci. 66:315–321. doi:10.4141/cjss86-032

Yao, R.J., J.S. Yang, and G.M. Liu. 2007. Calibration of soil electromagnetic conductivity in inverted salinity profiles with an integration method. Pedosphere 17:246–256. doi:10.1016/S1002-0160(07)60031-9