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Geophysical Techniques for Assessing Soil Salinity Across Multiple Scales

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Introduction

Soil salinity refers to the total salt concentration in the soil solution (i.e., the aqueous liquid phase of the soil and its solutes) consisting of soluble and readily dissolvable salts including charged species (e.g., Na+, K+, Mg2+, Ca2+, Cl−, HCO3−, SO42−, and CO32−), non-ionic solutes, and ions that combine to form ion pairs (Corwin, 2003). The primary source of salts in soil and water is the geochemical weathering of rocks from the Earth’s upper strata, with atmospheric deposition and anthropogenic activities serving as secondary sources. Salts accumulate in the root zone of agricultural soils primarily as a consequence of the process of evapotranspiration, which includes evaporation from the soil surface and plant transpiration. Evapotranspiration selectively removes water, leaving salts behind. Soil salinity can also accumulate as a consequence of poor irrigation water quality, poor drainage due to a high water table or low soil permeability, and topographic effects where an upslope recharge results in a downslope discharge of salts. In addition, salts can accumulate from saltwater spills associated with oil field activities, from high rates of manure and sludge applications, and from seawater intrusion in coastal areas.

There are a variety of agricultural impacts that salt accumulation in the root zone can have. Salts in the root zone can reduce plant growth, reduce yields, and, in severe cases, cause crop failure. Salinity impacts on plant yield occur for several reasons. Salinity limits plant water uptake by reducing the osmotic potential, making it more difficult for the plant to extract water. Salinity may also cause specific-ion toxicity (e.g., Na+ and Cl−) or upset the nutritional balance of plants. The composition of the salts in the soil solution influences the composition of cations on the exchange complex of soil particles, which subsequently influences soil permeability and tith.

The global impact of soil salinity is daunting. Squires and Glenn (2009) estimated the global extent of saline soils to be 412 Mha, which closely agrees with the FAO estimate of 397 Mha (http://www.fao.org/soils-portal/soil-management/management-of-some-problem-soils/salt-affected-soils/more-information-on-salt-affected-soils/en/). The estimate of Szabolcs (1989) is more conservative at 352 Mha. Of the estimated 230 Mha of irrigated land worldwide, from 20 to 50% may be salt affected (Szabolcs, 1992; Ghassemi et al., 1995; Flowers, 1999). Ghassemi et al. (1995) estimated that salinization of irrigated soils causes an annual global income loss of US$12 billion. Recent estimates of income loss due to salinity within California alone are US$ 3.7 billion for 2014 (Welle and Mauter, 2017). Soil salinity is a crucial soil chemical property for soil health and quality that is routinely measured and monitored due to its impact on agriculture.

Soil salinity exhibits complex, 3-dimensional spatial patterns within the root zone with a coefficient of variation generally over 80-90% (Corwin et al., 2003) and is highly temporally variable. The spatial complexity is clearly visible in the aerial image of precipitated salt patterns on the surface of a field shown in Figure 1. The mapping and monitoring of soil salinity from field to regional scales is crucial for crop selection, site-specific irrigation and salinity management, soil quality and health assessment, reclamation, and assessing degraded water reuse impacts, to mention a few.

Since 1980 the USDA-ARS U.S. Salinity Laboratory (USSL) has been the center of research related to mapping and monitoring soil salinity at field scale and larger spatial extents using electromagnetic induction (EMI) and electrical resistivity (ER) (Corwin, 2008). Over that time USDA-ARS scientists and scientists visiting USSL have developed three approaches for mapping soil salinity at three distinct spatial scales: field (<3 km²), landscape (3-10 km²), and regional (10-10⁵ km²) scales. Each approach is based on the measurement of apparent soil electrical conductivity (ECᵣ), which is the bulk conductivity of the soil and is a complex measurement influenced by a variety of soil properties, including salinity, texture, water content, bulk density, clay mineralogy, and organic matter. The three approaches are: (1) ECᵣ-directed soil sampling (field scale), (2) ANOCOVA approach (landscape scale), and (3) satellite imagery combined with ECᵣ-directed soil sampling (regional scale). A detailed discussion of the protocols for mapping soil salinity at field, landscape, and regional can be found in Corwin and Scudiero (2016).
Geospatial EC<sub>a</sub> Measurements

Geospatial EC<sub>a</sub> measurements are particularly well suited for establishing within-field spatial variability of soil properties because they are quick and dependable measurements that integrate the influence of several soil properties that contribute to the electrical conductance of the bulk soil. At present, no other measurement provides a greater level of spatial soil information than that of geospatial measurements of EC<sub>a</sub> when used to direct soil sampling (Corwin and Lesch, 2005a). However, EC<sub>a</sub> is a complex soil property that is influenced by a complex interaction of a variety of edaphic properties, including soil salinity (most commonly measured as the electrical conductivity of the saturated soil paste extract or EC<sub>e</sub>), texture (quantitatively approximated by saturation percentage or SP), water content (θ<sub>w</sub>), bulk density (ρ<sub>b</sub>), organic matter (OM), clay mineralogy, cation exchange capacity (CEC), and temperature (T). Measurements of EC<sub>a</sub> must be interpreted with these influencing edaphic factors in mind. Geospatial EC<sub>a</sub> measurements serve as a means of defining spatial patterns that indicate differences in electrical conductance due to the combined conductance influences of EC<sub>e</sub>, SP, θ<sub>w</sub>, ρ<sub>b</sub>, OM, CEC, and T.

There are three primary geophysical techniques for measuring EC<sub>a</sub> in the root zone (i.e., top 1.2 or 1.5 m): electrical resistivity (ER), electromagnetic induction (EMI), and time domain reflectometry (TDR). Electrical resistivity and EMI are easily mobilized and are well suited for field scale applications because of the ease and low cost of measurement with a volume of measurement that is sufficiently large (> 1 m<sup>3</sup>) to reduce the influence of local-scale variability. Developments in agricultural applications of ER and EMI have occurred along parallel paths with each filling a needed niche based upon inherent strengths and limitations. Even though TDR is a useful and well-studied technique for measuring EC<sub>a</sub>, it has lagged behind ER and EMI as an ‘on-the-go’ proximal sensor because it does not provide a continuous stream measurement with associated GPS positions. Rather, TDR requires the user to go from one location to the next, stopping at each location to take discrete measurements; consequently, it is less rapid and is less appealing for mapping EC<sub>a</sub> at field scales and larger spatial extents.

The characterization of spatial variability using geospatial EC<sub>a</sub> measurements is based on the hypothesis that spatial EC<sub>a</sub> information can be used to develop a directed soil sampling plan that identifies sites that adequately reflect the range and variability of soil salinity and/or other soil properties correlated with EC<sub>a</sub> at the site of interest. This hypothesis has repeatedly held true for a variety of agricultural applications (Corwin and Lesch, 2005a). Because EC<sub>a</sub> is influenced by a variety of edaphic properties, an understanding and interpretation of geospatial EC<sub>a</sub> data can only be obtained from ground-truth measures of soil properties that correlate with EC<sub>a</sub>, which results from either a direct influence or indirect association at the particular study site of interest. For this reason, geospatial EC<sub>a</sub> measurements are used as a surrogate of soil spatial variability to direct soil sampling when mapping soil salinity at field scales and larger spatial extents and are not generally used as a direct measure of soil salinity except in instances where salinity is dominating the EC<sub>a</sub> measurement.

Field-Scale Approach: EC<sub>a</sub>-Directed Soil Sampling

Scientists at the U.S. Salinity Laboratory have developed an integrated system for the measurement of field-scale spatial variability, particularly salinity, consisting of (1) guidelines and protocols for the characterization of soil spatial variability using EC<sub>a</sub>-directed soil sampling presented by Corwin and Lesch (2003, 2005b) and protocols specific to soil salinity assessment presented by Corwin and Lesch (2013), (2) mobile EC<sub>a</sub> measurement equipment (Rhoades, 1993), and (3) sample design software (Lesch et al., 2000; Lesch, 2005). The integrated system and procedure for mapping soil salinity at field scale is schematically illustrated in Figure 2.
The protocols for an ECₐ-directed soil sampling survey to measure soil salinity at field scale include 8 steps (Corwin and Scudiero, 2016): (1) ECₐ survey design, (2) geo-referenced ECₐ data collection, (3) soil sample design based on geo-referenced ECₐ data, (4) soil sample collection, (5) physical and chemical analysis of pertinent soil properties, (6) spatial statistical analysis, (7) determination of the dominant soil properties influencing the ECₐ measurements at the study site, and (8) GIS development.

As indicated in Figure 2, maps of soil salinity can be created by interpolating the salinity from soil samples (i.e., ‘hard’ salinity data alone) or from a calibration equation (see below Eq. [1]) relating soil salinity to EMI measurements of ECₐ in the vertical (EMᵥ) and horizontal coil configurations (EMᵥ and EMₕ) and x-y location (i.e., easting and northing) in the field to account for any spatial trend across the field due to anthropogenic or pedogenic influences (i.e., using ‘hard’ salinity and ‘soft’ ECₐ data in combination):

$$\ln(\text{EC}_e) = \beta_0 + \beta_1 \ln(\text{EM}_v) + \beta_2 \ln(\text{EM}_h) + \beta_3(x) + \beta_4(y) + \epsilon$$

where ECₑ is the soil salinity or electrical conductivity of the saturation extract (dS m⁻¹); β₀, β₁, β₂, β₃, and β₄ represent the empirical regression model coefficients; x and y are the easting and northing UTM coordinates (m), and ε is the error term. Figure 3 shows a typical map of an ECₑ survey (i.e., geospatial EMᵥ and EMₕ ECₐ measurements) for a 32.4-ha saline-sodic field with sample site locations (circle symbol) directed by geospatial ECₐ measurements and a map of the soil salinity (ECₑ) estimated from a calibration equation, i.e., Eq. [1].

![Westlake Farms, Stratford, CA (August 2012)](image)

Landscape-Scale Approach: Analysis of Co-Variance (ANOCOVA)

Multiple-field ECₐ survey data often exhibit an abrupt change in magnitude across field boundaries, generally a consequence of anthropogenic influences, such as crop and irrigation management, and often times pedogenic influences. This presents a challenge to the conversion of ECₐ to ECₑ at spatial extents of thousands to tens of thousands of hectares (i.e., landscape scale). The abrupt change is caused by various reasons: (i) between-field variation in field average water content due to irrigation method, frequency, and timing; (ii) between-field variation in soil texture; (iii) condition of the soil surface (e.g., till vs. no-till) due to management practices that effect soil compaction; (iv) surface geometry (i.e., presence or absence of beds and furrows); (v) temperature differences (i.e., ECₐ surveys conducted at different times of the year); and (vi) between-field spatial variation in salinity (Corwin and Lesch, 2014).

Calibration models are often used to adjust out an abrupt change. Consider the case of surface geometry, i.e., presence and absence of beds and furrows in a field, where an ECₐ survey has been conducted. In the absence of any surface geometry, a simple power model describes the deterministic component of the ECₑ – ECₐ calibration relationship, i.e.,

$$EC_{e,i} = \beta \cdot EC_{a,i}^i$$

where β is a coefficient and i = 1, 2, 3, . . . , n. To account for the surface geometry effect an additional variable (x) and associated scaling parameter (θ) are used, i.e.,

$$EC_{e,i} = \theta \cdot EC_{a,i}^i \cdot \text{EGF}(x)$$

where x = 1 if there is a surface geometry effect and x = 0 otherwise. Under a log transformation, this multiplicative parameter becomes additive as shown in Eq. [2]:

$$\ln(EC_{e,i}) = x \ln(\theta) + \ln(\beta) + \alpha \ln(EC_{a,i})$$

[2]

On a log – log scale, a simple linear regression model with an additional blocking (shift) parameter can adjust an abrupt change in any multiplicative ECₐ effect within a field. Equation [2] is a type of analysis of co-variance (ANOCOVA) model. In principle, this type of ANOCOVA modeling approach could be used to calibrate multiple-field ECₐ surveys to ECₑ provided the assumptions in Eq. [2] are reasonable.

If geo-referenced ECₐ survey data is acquired across multiple fields and assume that the number of soil sampling locations collected in any given field is minimal (i.e., n < 10). In the absence of any useful spatial or geostatistical modeling approach under these conditions, basic regression modeling techniques are used such as ANOCOVA. An ANOCOVA model for ECₑ – ECₐ calibration is defined by Eq. [3]:

$$\ln(EC_{e,j,k}) = \beta_{0,j,k} + \beta_{1,j} \ln(EM_{v,j,k}) + \beta_{2,j} \ln(EM_{h,j,k}) + \epsilon_{j,k}$$

[3]

where i refers to the soil sample site within a field (i = 1, 2, 3, . . . , nᵢ), j is the sample depth (j = 1, 2, 3, . . . , p), k is the field (k = 1, 2, 3, . . . , M), EMᵥ is the ECₐ measured with EMI in the vertical coil configuration (dS m⁻¹), and EMₕ is the ECₐ measured with EMI in the horizontal coil configuration (dS m⁻¹). In the ANOCOVA model, the intercept parameter is uniquely estimated for each sampling depth and field, but the slope coefficients are only assumed to change across sampling depths (not across fields).
The ANOCOVA approach for EC_a – EC_e calibration has been validated at regional-scale (Corwin and Lesch, 2016). However, the practical application of the ANOCOVA approach is best used at landscape scale, i.e., 3-10 km² (Corwin and Lesch, 2016; Scudiero et al., 2016a).

Regional-Scale Approach: Satellite Imagery

At the regional-scale, spatial patterns of soil salinity are influenced by several factors, including: pedogenic, meteorological, hydrological, topographical, agronomic, anthropogenic and edaphic factors. In general, agronomic management influences local-scale salinity, whereas anthropogenic and pedogenic factors influence landscape-scale salinity. To model such multi-scale variations, covariates offering continuous spatial coverage, such as remote sensing data, are ideal. In the past three decades, two remote sensing approaches have been developed for mapping soil salinity. The most popular approach includes a variety of spatial analyses of surface (bare-) soil reflectance. The other consists of the indirect assessment of root-zone soil salinity through the study of plant canopy reflectance. Salt accumulation at the soil surface often results in the formation of white salt crusts. Such crusts are easily identifiable with remote sensing as their reflectance properties are different from those of soils not affected by soil salinity (Mougenot et al., 1993). One way to identify crusts is through image classification (e.g., Metternicht, 1998). Often, salt efflorescence is partial, making the identification of salt-affected bare-land more problematic. This is because of confounding effects from different soil types (e.g., texture, color), soil roughness, presence of vegetation, and surface soil water content. However, most of these confounding effects can be accounted for (e.g., Xu et al., 2016). Unfortunately, this approach has limited relevance in agricultural applications because crop growth and yield are influenced by the salinity in the root-zone. In agriculture, information of surface soil salinity is often only relevant for evaluation of plant germination. Indeed, several studies show that there is no direct correlation between root-zone and surface soil salinity (e.g., Zare et al., 2015).

Spectral reflectance properties of salt-affected vegetation are different from those of non-stressed plants. Differences can be seen in the spectral signature of crops, especially in the visible (e.g., 450-700 nm) and near-infrared (e.g., 770-900 nm) spectra. Plants stressed by soil salinity are characterized by higher visible and lower near-infrared range reflectance than non-stressed plants. Unfortunately, the use of surface reflectance (i.e., multi and hyperspectral) from a single satellite scene to model soil salinity is site-specific, for reasons including: (1) the spectral signature of a crop changes with phenological stages; (2) different crops are characterized by different spectral signatures; (3) other stress sources, such as nutrient deficiency or water stress, trigger similar responses in plants reflectance properties; and (4) surface reflectance is influenced by different soil backgrounds. Due to these confounding effects, regional-scale mapping of soil salinity with remote sensing has often yielded unsatisfactory and inconsistent results in the past.

Recent research, reviewed by Scudiero et al. (2016b), showed that salinity stress can be isolated from other types of within-season and season-wide transient stressors (e.g., water stress mismanagement) by analyzing multi-year canopy reflectance data (e.g., Lobell et al., 2010; Scudiero et al., 2015). Scudiero et al. (2015) considered annual average values of Landsat 7 (USGS and NASA, USA) vegetation indices from seven years, and used the year with highest vegetation index value (i.e., year with maximum average plant performance) to build a regression model from ground-truth fields located in California’s western San Joaquin Valley. The regional-scale salinity model included co-variate information on land use (i.e., cropping system) and meteorology. Figure 4 shows the map of soil salinity for the west side of the San Joaquin Valley using the regional-scale salinity model.

![Figure 4: Map of soil salinity within the root zone (0-1.2 m) for the west side of the San Joaquin Valley for 2013. Source: Scudiero et al. (2017) with permission.](image-url)
er, the approach has some limitations, including: uncertainty in the depth of the modeled soil profile (because different crops have different root-zone depths) and uncertainty of predictions at very low salinity values. At low salinity levels, most crops are not influenced by soil salinity (Maas and Hoffman, 1977), making it impossible to assess the underlying soil salinity through canopy reflectance. The growth of halophytes (salt tolerant) weeds is not optimal at low salinity levels (BOSTID, 1990), making it hard to discriminate between low halophyte plant performances at low (i.e., not stressed) and high (i.e., stressed) salinity levels (Scudiero et al., 2015; Zhang et al., 2015).

Knowledge Gaps in Salinity Assessment Research

Salinity assessment based on EC_a-directed soil sampling has been used for a variety of applications including: mapping and monitoring soil salinity (Lesch et al., 1992; Corwin and Lesch, 2013), mapping soil quality (Corwin et al., 2003), monitoring management-induced changes to soil properties during reclamation (Corwin et al., 2006), delineating site-specific management units (Corwin and Lesch, 2010), assessing degraded water reuse impacts on soil health (Corwin, 2012; Corwin and Ahmad, 2015), modeling non-point source pollutants in the vadose zone (Corwin et al., 1999), conserving water (Corwin, 2015), characterizing soil spatial variability (Corwin and Lesch, 2005b, 2005c), and regional-scale salinity inventory (Lobell et al., 2010; Scudiero et al., 2015). Even so, there are knowledge gaps in multi-scale salinity assessment research that need to be filled to make the methodology more robust in its application. These gaps are focused primarily on (1) refining field-scale EC-a-directed soil sampling protocols under conditions of drip and micro-sprinkler irrigation, (2) inverse modeling to obtain soil salinity profiles and 3-D salinity maps, and (3) refinements in regional-scale salinity assessment.

Field-scale EC_a-directed soil sampling protocols are designed to minimize soil sampling by using the spatial variation in EC_a measurements to select soil sample sites that will reflect the variation and range in EC_a without clustering the sample sites. This approach works well under conventional sprinkler and flood irrigation systems, but breaks down under drip and micro-sprinkler irrigation due to the high level of local-scale variation that is found within distances < 1 to 2 m; as a consequence, the EC_a – EC_e calibration is seldom reliable. Addition research is needed to develop reliable protocols for fields under drip and micro-sprinkler irrigation systems.

A research trend in salinity assessment has been the characterization of salinity profiles and 3-D mapping of salinity using inverse modeling of geospatial EC_a measurements. Characterizing salinity profiles in the root zone from EC_a measurements began with the work of Rhoades, Corwin, and Hendrickx (Rhoades and Corwin, 1981; Corwin and Rhoades, 1982, 1983, 1990; Hendrickx et al., 2002), but has been significantly improved by Triantafilis and colleagues to the point of the creation of quasi 3-D EC_a maps (Triantafilis and Santos, 2010; Huang et al., 2017). Validation of this approach is still underway, but the potential to create reliable 3-D maps of soil salinity is certainly within the foreseeable future.

Even though significant advances have been made in the past few years, regional-scale salinity assessment is still in its infancy. A comprehensive validation of regional-scale salinity assessment is needed to support the credibility of the methodology. Additional fine tuning of regional-scale salinity models, such as for the San Joaquin Valley, is also needed through the inclusion of co-variates such as orchards and vineyards and higher resolution spatial data for texture.

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