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Simplifying field-scale assessment of spatiotemporal changes of soil salinity

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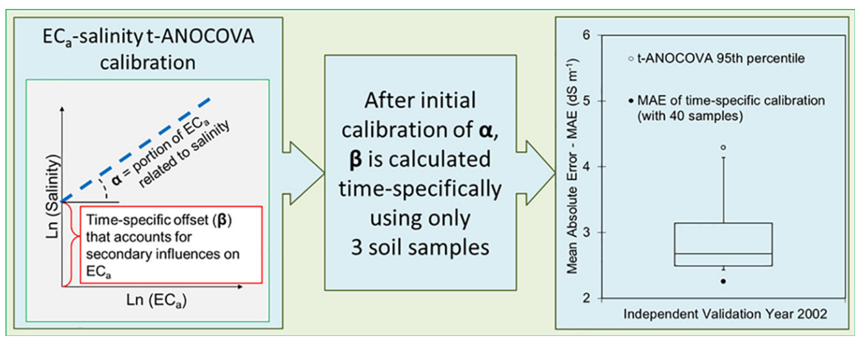
HIGHLIGHTS

- Calibrated apparent electrical conductivity (EC_a) can be used to estimate soil salinity.
- A t-ANOCOVA calibration was used to monitor salinity using limited soil sampling.
- The t-ANOCOVA calibration was compared to established EC_a calibration approaches.
- The t-ANOCOVA calibration was reliable, especially at low salinity values.

GRAPHICAL ABSTRACT



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ABSTRACT

Monitoring soil salinity (EC_e) is important for planning and implementing agronomic and irrigation practices. Salinity can be measured through soil sampling directed by geospatial measurements of apparent soil electrical conductivity (EC_a). Using data from a long-term (1999–2012) monitoring study at a 32.4-ha saline field located in California, USA, two established field-scale approaches to map and monitor soil salinity using EC_a are reviewed: one that relies on a single EC_a survey to identify locations that can be repeatedly sampled to infer the frequency distribution of EC_e; and another based on repeated EC_a surveys that are calibrated, each time, to EC_e estimation using ground-truth data from soil samples. The reviewed approaches are very accurate and reliable, but require extensive soil sampling. Subsequently, we propose a novel approach – temporal analysis of covariance (t-ANOCOVA) modeling – that results in accurate spatiotemporal salinity estimations using EC_a surveys with a significant reduction in the number of soil samples needed for calibration of EC_a to EC_e. In this modeling framework, the EC_e-EC_a relationship is described with a log-transformed linear function. The regression slope indicates the magnitude of the contribution of EC_e to EC_a and is assumed to remain constant over time, while the intercept represents the secondary factors influencing EC_a that are not related to EC_e (e.g., soil tillage). Once the t-ANOCOVA slope is established for a field, in subsequent surveys as few as three soil samples are used to estimate a time-specific t-ANOCOVA intercept so that EC_a measurements can be converted to EC_e estimations. Our results suggest that this approach is reliable at

Abbreviations: t-ANOCOVA, temporal analysis of covariance; EC_a, apparent soil electrical conductivity (dS m^{-1}); EC_e, electrical conductivity of the saturation extract (dS m^{-1}); EM_h, electromagnetic induction measurement in the horizontal coil configuration; EMI, electromagnetic induction; EM_v, electromagnetic induction measurement in the vertical coil configuration; MAE, mean absolute error; OLS, ordinary least squares; RSSD, response surface sampling design; SSMU, site-specific management units; TSC, time-specific calibration; WSJV, west side of the San Joaquin Valley.

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low salinity values (i.e., where common crops can grow). The t-ANOCOVA approach requires further validation before real-world implementations, but represents a significant step towards the use of EC_a mobile sensor technology for inexpensive soil salinity monitoring at high temporal resolution.

1. Introduction

Managing agricultural soil salinity is crucial to sustaining future food production. Soil salinity strongly limits global crop yields (FAO and ITPS, 2015). Over 20% of global irrigated farmland is affected by soil salinity (Tanji and Wallender, 2012; Wicke et al., 2011). More than half of that 20% belongs to four countries: China, India, Pakistan, and the United States of America (FAO and ITPS, 2015). Salinity is typically managed by irrigating soils beyond the consumptive water use of plants, leaching from the root zone soluble salts that would otherwise harm plant growth (e.g., sodium, chloride) due to osmotic effects, specific ion toxicity effects, nutrient imbalances, and influences on tilth and permeability. Reliable information on salinity levels of the soil root-zone (e.g., 0 to 0.9–1.5 m depth) is essential for developing salinity management strategies, particularly when water resources are limited.

The complex spatial patterns of salinity usually found on agricultural lands (Lesch et al., 1992) make it difficult to map salinity using grid or random sampling since tremendous numbers of samples (e.g., hundreds per field) are necessary. Clearly, there is a cost issue related to monitoring the spatiotemporal changes of soil salinity at field scale (e.g., <1 km^2) over multiple fields. By using soil apparent electrical conductivity (EC_a, dS m^{-1}) measurements from mobile on-the-go sensors, expenses can be notably lowered (Lesch, 2005). Soil EC_a is influenced by several properties, including: water content, texture, and soil salinity (Corwin and Lesch, 2005; Doolittle and Brevik, 2014). To estimate salinity, EC_a measurements must be site-specifically calibrated to ground-truth measured soil salinity, generally measured as electrical conductivity of the saturation extract (EC_e), by establishing a linear model between EC_e and EC_a (Lesch, 2012). Because it can be easily mobilized and coupled with GPS systems, EC_a is measured intensively with tens of thousands of sampling locations per field.

Geospatial EC_a measurements serve as a surrogate to characterize the spatial variability of soil properties correlated to EC_a at a given site (Corwin and Lesch, 2003; Corwin and Lesch, 2005). In instances where salinity dominates the EC_a measurement (i.e., $EC_a > 2$ dS m^{-1}), the spatial variability of EC_a will represent the spatial variability of soil salinity (Corwin and Lesch, 2013). Therefore, the EC_a surveys can be used to select representative (in terms of inferential statistics) soil sampling locations that will reflect the range and spatial variation in georeferenced EC_a measurements (Corwin and Lesch, 2005). Model-based sampling design algorithms, such as the response surface sampling design (RSSD) (Lesch et al., 2000; Lesch, 2005), can be used to identify the optimal representative soil sampling locations. The RSSD identifies soil sampling locations so that the frequency statistics of the ancillary information used, be it EC_a (Lesch, 2005) or remote sensing imagery (Fitzgerald et al., 2006) or radar data (Guo et al., 2015), is fully represented. Concurrently, the RSSD maximizes the distance between selected soil sampling locations. This latter step is directed to avoid (short-scale) autocorrelation of ordinary least squares (OLS) regression residuals (Hengl et al., 2003; Lesch and Corwin, 2008).

The first objective of this manuscript is to discuss two established approaches in which geospatial measurements of EC_a are used to monitor soil salinity at field scale. The first methodology consists of using an initial EC_a survey to identify representative soil sampling locations that are sampled for EC_e over time at selected time intervals. The other consists of surveying the field for EC_a at each sampling time and then calibrating the sensor readings using soil samples taken at the time of the EC_a survey. If the spatial EC_a patterns are unchanged, then the sample locations are the same as those determined in the first EC_a survey. If the spatial EC_a patterns have changed, then new sample locations are identified that reflect the range and spatial variability of the new EC_a survey.

The second objective is to propose a novel salinity monitoring approach based on the assumption of temporal covariance (t-ANOCOVA) of the EC_e-EC_a relationship, which should allow reducing the number of soil samples needed at each monitoring time. The t-ANOCOVA is a temporal application of the ANOCOVA EC_e-EC_a calibration model presented by Corwin and Lesch (2014) and later validated by Corwin and Lesch (2016) and Scudiero et al. (2016). After an initial calibration that requires from a half to several dozen soil samples per field depending on the extent of the variability, the t-ANOCOVA approach only requires as few as three soil samples to calibrate the EC_a measurements taken at subsequent monitoring times.

2. Theoretical background

2.1. Temporal covariance of the EC_e-EC_a relationship

Apparent soil electrical conductivity measurements can be expressed as a multiplicative function of salinity, water content, and soil tortuosity, which depends on several soil properties, including soil texture, particle pore distribution, density and particle geometry, and organic matter content. According to Archie's Law (Archie, 1942), and other similar models (e.g., Rhoades et al. [1976]), EC_a may be expressed as a function of pore-water salinity (EC_p), soil water content, and other soil-specific parameters:

$$EC_a = \frac{EC_p \times \phi^m \times S^n}{k} \tag{1}$$

where ϕ is soil porosity, S is the relative saturation, and k, m, and n are fitting parameters that are dependent on soil texture, organic carbon content, and other physical and chemical properties (Allred et al., 2008). However, Eq. (1) is not applicable when soil is too dry because the water pathways for electrical conductivity are not continuous. As a rule of thumb, Corwin and Lesch (2013) suggest that volumetric water content should be at least 70% of field capacity when the EC_a survey is carried out.

Because the pore-water electrical conductivity, EC_p, can generally be expressed as a linear function of the total ion content in the soil (Rhoades et al., 1989), salinity (EC_e) can be expressed as a function of EC_a with a multiplicative error model (Corwin and Lesch, 2014):

$$EC_e = \beta \times EC_a^{\alpha} \times \varepsilon^* \tag{2}$$

where α and β are coefficients that subsume ϕ, S, k, m, and n; and ε^* is a multiplicative error component. In Eq. (2), the error component is a function of the ratio between EC_e and the explanatory term of the equation (Baskerville, 1972; Tian et al., 2013).

After a log transformation of Eq. (1), the EC_a-EC_e relationship is:

$$\ln(EC_e) = \ln(\beta) + \alpha \times \ln(EC_a) + \varepsilon \tag{3}$$

where ε is a random additive error component, equal to $\ln(\varepsilon^*)$. Eq. (3) can be parameterized using an OLS approach, provided the underlying assumptions (including residuals being normally distributed and spatially independent) are respected (Lesch and Corwin, 2008).

The influence of salinity on EC_a readings is reflected in the slope (α) of Eq. (3). The effects not due to salinity but to other soil properties (e.g.,