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Validating the use of MODIS time series for salinity assessment over agricultural soils in California, USA

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ABSTRACT

Testing soil salinity assessment methodologies over different regions is important for future continental and global scale applications. A novel regional-scale soil salinity modeling approach using plant-performance metrics was proposed by Zhang et al. (2015) for farmland in the Yellow River Delta, China, a region with a humid continental/subtropical climate. The one-year integral of temporally interpolated MODIS Enhanced Vegetation Index (EVI) time series data was proposed as an explanatory variable for agricultural soil salinity modeling. Here, we test such a methodology in California's Central Valley, USA, a region with a semi-arid Mediterranean climate. Time series of EVI, Normalized Difference Vegetation Index (NDVI), and Canopy Response Salinity Index (CRSI) were created for the 2007–2013 period. Seventy-three MODIS pixels surveyed for 0–1.2-m soil salinity in 2013 were used as the ground-truth dataset. Our results validate the tested approach: the 2013 integral of CRSI (best performing index) had a Pearson correlation coefficient (r) of -0.699 with salinity. Results obtained using temporally integrated data were almost always better than those obtained using individual data. Furthermore, we show that the methodology can be improved by the use of multi-year data. Further research is needed to improve spatial resolution and the selection of vegetation indices.

1. Introduction

1.1. Soil salinity and agriculture

Elevated levels of soluble salts (e.g., Cl^-, Na^+) in soils are a major threat to irrigated and rain-fed agriculture worldwide (Ghassemi et al., 1995; Metternicht and Zinck, 2003; Ivits et al., 2011). Even when present in small amounts, soluble salts reduce yields for many crops. According to the U.S. Salinity Laboratory (US Salinity Laboratory Staff, 1954), most agricultural plants cannot grow if soil salinity exceeds $16\ dS\ m^{-1}$, where salinity is quantified as the electrical conductivity of a saturated soil paste extract (EC_e). Soils are classified as saline when $EC_e > 4\ dS\ m^{-1}$. About 23% (ca. 0.34×10^9 ha) of worldwide farmland is estimated to be saline (ITPS: Intergovernmental Technical Panel on Soil, 2015). Knowledge and mapping of the spatial distribution of soil salinity is important for irrigation and drainage management, and for setting water and environmental policies that affect the economic sustainability of farming systems (Lambert and Southard, 1992; Letey, 2000; Welle and Mauter, 2017).

Many geological (e.g., pedogenesis), geomorphological (e.g., elevation gradients), meteorological (e.g., rainfall and evapotranspiration totals), and management (e.g., irrigation management) factors affect the salinity levels of irrigated soils (Elnaggar and Noller, 2009; Akramkhanov et al., 2011; Scudiero et al., 2014a; Vermeulen and Van Niekerk, 2017). This multiplicity of contributing factors makes it extremely difficult to extrapolate local point measurements of soil salinity to regional scales. Satellite based imagery can be used as a covariate in salinity mapping models (Wu et al. 2014) because it captures variations of salinity at different scales (e.g., subfield and between fields variations) (Scudiero et al., 2017).

Abbreviations: CRSI, canopy response salinity index; EC_e, electrical conductivity of the saturation extract ($dS\ m^{-1}$); EVI, Enhanced Vegetation Index; NDVI, Normalized Difference Vegetation Index; SG, Savitzky–Golay; VI, vegetation index; WSJV, western San Joaquin Valley; YI, yearly integral

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1.2. Remote sensing of soil salinity

1.2.1. Surface salinity versus root-zone salinity

Salinity at or near the soil surface (~ top 0.05–0.1 m) can be readily identified over large regions using remote sensing tools (Allbed and Kumar, 2013). However, monitoring surface salinity is of limited interest for agricultural applications. Especially in irrigated agriculture, salinity generally accumulates deeper in the soil profile. Other than during germination, crops are influenced by soil conditions over the entire root zone, which can extend down to 0.5–1.2 m and deeper depending on the crop. For example, Lobell et al. (2007) found that in the Colorado River Delta region, Mexico, soil salinity levels at 0.3–0.6 m had a higher impact on plant growth than salinity at 0–0.3 m. Determining root zone soil salinity from surface measurements is challenging: often, there is not a direct correlation between surface and root-zone soil salinity (e.g., Zare et al., 2015).

Over large regions, indirect measures of root zone soil salinity can be obtained through measurements of crop performance (e.g., greenness). Visible, near infrared, infrared, and thermal reflectance can be used as a measure of salinity stress (Lobell et al., 2010; Wu et al., 2014; Zhang et al., 2015; Ivushkin et al., 2017). However, other stressors (e.g., water deficiency, pests, and nutrient deficiency) trigger similar canopy reflectance responses (e.g., higher reflectance in the visible range and lower in the infrared). Additionally, other factors, such as phenological stage, also influence canopy reflectance (Solari et al., 2008; Tagarakis and Ketterings, 2017), thus further obscuring the relation between reflectance and salinity. Multi-temporal analysis of canopy reflectance can be used to isolate the effects of soil salinity from other confounding factors (Lobell et al., 2010; Wu et al., 2014). This is possible when average root zone salinity remains fairly stable over a short period of time – up to 5–7 years (Lobell et al., 2007; Lobell et al., 2010). Conversely, other stressors (e.g., mismanagement, pests) tend to be more transient, often varying intra-annually (Scudiero et al., 2014b).

1.2.2. Detecting soil salinity with MODIS time series vegetation index data

In the last ten years, multi-temporal remote sensing data, especially visible and near-infrared reflectance, has been used in several studies to detect soil salinity (Lobell et al., 2007; Platonov et al., 2013; Wu et al., 2014; Scudiero et al., 2016b, Gorji et al., 2017). One of the most noteworthy studies was done by Zhang et al. (2015). They used Moderate Resolution Imaging Spectroradiometer (MODIS, The National Aeronautics and Space Administration – NASA, USA) time series vegetation index (VI) data. They proposed that salinity estimates from VI time-series could be improved by simulating the inter-annual VI variations through a temporal interpolation procedure. By doing so, information on crop physiology (such as seasonal integrals of VI values) can be extracted from the time series datasets and used as explanatory variables in salinity assessment models. Zhang et al. (2015) developed their methodology using ground data from the Yellow River Delta in the Dongying District, China, which encompasses a mix of humid continental and humid subtropical climates with dry winters and rainy summers, with yearly average rainfall of 600 mm (Zhang et al., 2011; Zhang et al., 2015). They reported that soil salinity correlated more strongly with integrals of VI time series (from a single growing season) than with VI from single dates. The VIs used by Zhang et al. (2015) were the Normalized Difference Vegetation Index, NDVI shown in Eq. (1) (Rouse et al., 1973):

$$\mathrm{NDVI} = \frac{(\mathrm{NIR}-\mathrm{R})}{(\mathrm{NIR} + \mathrm{R})} \tag{1}$$

where R and NIR are MODIS's red (620–670 nm) and near-infrared (841–875 nm) bands, respectively; and the Enhanced Vegetation Index, EVI shown in Eq. (2) (Huete et al., 2002):

$$\mathrm{EVI} = g \times \frac{(\mathrm{NIR}-\mathrm{R})}{(\mathrm{NIR}+c_1 \times R - c_2 \times \mathrm{B} + l)} \tag{2}$$

where B is MODIS's blue (459–479 nm) band and g, c_1, c_2, and l are aerosol and soil correcting parameters set to 2.5, 6, 7.5, and 1 respectively. They found that the one-growing-season time series integral of EVI was more strongly correlated with soil salinity and more sensitive to salinity changes than the integral of NDVI was.

1.2.3. Justification for this research

The research of Zhang et al. (2015) and other previously published regional scale salinity assessment research has been carried out over areas with fairly homogeneous meteorology (e.g., rainfall, temperature) and geomorphology (e.g., pedogenesis). Future research efforts should focus on creating national and global inventories of agricultural soil salinity (Scudiero et al., 2016a). Mapping salinity at such broad scales would entail using remote sensing over diverse geographical regions. As a step towards that goal, the current remote sensing approaches, such that proposed by Zhang et al. (2015), should be tested and validated over different geographical regions of the world.

1.2.4. Research objectives

In this study, we test the MODIS VI time-series approach proposed by Zhang et al. (2015). We evaluate the approach using a ground-truth soil salinity dataset from the western San Joaquin Valley, California, USA (Scudiero et al., 2014a), a region very different from the Yellow River Delta. Besides testing the approach of Zhang et al. (2015), we also address the following questions:

1. Should the integral value of the MODIS VI time series proposed by Zhang et al. (2015) be preferred to a seasonal average of the VIs?
2. Should multiple-year time series of MODIS VIs data be used to map salinity over semi-arid farmland, such as in California's western San Joaquin Valley, rather than single-season time series? A single year of data might not be sufficient to isolate the effect of salinity on crop metrics. In a given year, crop performance may be limited by other factors besides salinity. In that case, a multi-year analysis may be required.
3. Does MODIS EVI provide better relationships with salinity in semi-arid farmland than NDVI, as observed for continental and sub-tropical climates by other authors, including Zhang et al. (2015)?
4. Are there relevant scale-related limitations for the use of MODIS VIs over areas with fairly heterogeneous cropping and land use patterns, such as California's western San Joaquin Valley?

2. Materials and methods

2.1. Study area

The farmland of California's western San Joaquin Valley (WSJV, Fig. 1a) is among the most salt-affected in California (Backlund and Hoppes, 1984; Lambert and Southard, 1992). The WSJV has hot and dry summers and cool winters. Annual rainfall averages around 150–200 mm. For WSJV, the 2011 National Land Cover Database classified 0.83×10^6ha as farmland (Fry et al., 2011). According to the CropScape database (Han et al., 2012), 16.2% of WSJV farmland was cropped with orchards in 2013 (e.g., *Pistacia vera* L., *Prunus dulcis* Mill.). The rest was used for herbaceous/annual (e.g., *Solanum lycopersicum* L., *Triticum aestivum* L.) crop production (75%), for pastureland (3.3%), or left fallow (21.6%). During the 2011–2015 California drought (Williams et al., 2015), the portion of fallow land increased steadily, from 11.8% pre 2011 to 33.7% in 2015 (Scudiero et al., 2017), mostly at the expense of herbaceous crop production (Howitt et al., 2014). Farmers' decisions on land fallowing were mainly driven by surface and well-water availability and by expected revenues (Howitt et al., 2014). Scudiero et al. (2017) reported that 55% of the farmland in WSJV (excluding orchards – which were not included in theirs study) is moderately to extremely affected by soil salinity.