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Modeling salinity effects on soil reflectance under various moisture conditions and its inverse application: A laboratory experiment

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ABSTRACT

Soil salinization is an important desertification process that threatens the stability of ecosystems, especially in arid lands. Quantifying and mapping soil salinity to monitor soil salinization is difficult because of its large spatial and temporal variability. There has been a growing interest in the use of hyperspectral reflectance as a rapid and inexpensive tool for soil salinity characterization in the recent past. However, as soil moisture often jointly affects soil reflectance, a moisture-insensitive reflectance model is needed to provide the base for soil salinity monitoring from soil reflectance. In this paper, we developed an exponent reflectance model to estimate soil salt contents inversely under various soil moisture conditions, based on a control laboratory experiment on the two factors (soil salinity and soil moisture) to soil reflectance. Main soil salt types (Na_2SO_4, NaCl, Na_2CO_3) with wide soil salinity (0% to 20%) and soil moisture (1.75% to 20%) levels (in weight base) from Western China were examined for their effects on soil reflectance through a model based approach. Moisture resistant but salt sensitive bands of reflected spectra have been identified for the model before being applied to inversely estimate soil salt content. Sensitive bands for Na_2SO_4 type of salt affected soils were identified as from 1920 to 2230 nm, and 1970 to 2450 nm for NaCl, 350 to 400 nm for Na_2CO_3 type of salt affected soils, respectively. The sensitive bands focused on ranged from 1950 to 2450 nm when all data were considered when ignoring salt types. The model was then applied to inversely estimate soil salt contents. High R^2 of 0.87, 0.79, and 0.66, and low mean relative error (MRE) of 16.42%, 21.17%, and 27.16%; have been obtained for NaCl, Na_2SO_4 and Na_2CO_3, respectively. Performance of the inverse model dropped but remained significant when ignoring salt types with an R^2 of 0.56 and a MRE of 33.25%. The approach proposed in this study should thus provide a new direction for estimating salinity from reflectance under various soil moisture conditions and should have wide applications in future monitoring of soil salinization.

1. Introduction

Soil salinization is one of the most common land degradation processes in arid and semi-arid regions and seriously damages ecosystem functions. Due to expanding population, more dry lands are being converted for agricultural production and this can only be achieved through irrigation, which consequently causes the expanding of salinization hazard (Metternicht and Zinck, 2003). Increase in salt concentrations results in many major soil degradation phenomena such as soil dispersion, sealing, crust formation, and loss of structure (Agassi et al., 1981; De Jong, 1994; Metternicht and Zinck, 2003), leading to reduced crop yield and agricultural production (FAO, 1988). It has been estimated that close to 1 billion hectares in general or 7% of the earth's continental extent are naturally salt-affected areas (Ghassemi et al., 1995). In addition, another 20% or worse of the world's irrigated lands are affected by salts (Ghassemi et al., 1995) and the proportion will keep increasing due to the increasing population pressure (Metternicht and Zinck, 2003). It is therefore paramount to find ways of stopping this tendency and combat the effects of soil salinization.

Early identification of salt-affected areas and monitoring are essential for sustainable agricultural management, which are vital for making timely and proper decisions for halting soil salinization. Although conventional techniques are available for identifying and monitoring soil salinization, these techniques are expensive, time-consuming and require intensive sampling to characterize spatial variability (Nanni and Dematte, 2006; Shepherd and Walsh, 2002). Therefore, more cost-effective methods for mapping soil salinity are required for broad-scale quantitative evaluation. Compared with conventional techniques for measuring soil salinization, remote sensing has many advantages on the contexts of high temporal sampling frequency and rapid nondestructive characterization of a wide range of materials.

A variety of remote sensing data and techniques have been applied successfully for identifying and monitoring soil salinization (e.g., Farifteh et al., 2006; Metternicht and Zinck, 2003), but are usually in

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heavy salt-affected soils. In slightly and moderately affected areas, the potentiality of remote sensing is usually restricted (Farifteh et al., 2006). Many studies have shown that hyperspectral data can be used to quantify characteristics of saline soils at various scales (Ben-Dor et al., 2002; De Jong, 1992; Dehaan and Taylor, 2003; Everitt et al., 1988; Farifteh et al., 2006; Metternicht and Zinck, 2003). Field application of hyperspectral remote sensing, however, has been limited by problems associated with soil moisture, especially in areas such as Western parts of China where similar soil texture, rare vegetation, and cloudlessness weather allow otherwise perfect applications of hyperspectral data to quantify soil salinity.

Soil is a complex composite of various mineral, water, air, and organic matter, which interferes with incoming light through inherent optical properties of its various components and the way they are arranged within the soil. Among those compositional variables, soil water is a principle component affecting soil reflectance spectra. The accuracy of quantifying soil salt and other mineral contents from soil reflectance is significantly influenced by the presence of water in the pore space and as particle film (Liu et al., 2002). It is widely known that the presence of water will darken the soil surface, primarily due to the change in the real part of the refractive index (n) of the immersion medium from air ($n=1$) to water ($n=1.33$) (Twomey et al., 1986), which has decreased the contrast between soil particles ($n\approx1.5$) and their surrounding medium and thus increasing the forward scattering and absorption probability (Lobell and Asner, 2002). Moisture contents of soils and salts (depending on the types) have similar affects on soil reflectance spectra and causes large anomalies in predicting salinity levels from remotely sensed data (Csillag et al., 1993). Moreover, soil moisture has been recognized as a main factor leading to the temporal change of soil reflectance (Liu et al., 2002) and hence further increases the difficulties of monitoring soil salt in time. Although hyperspectral remote sensing has been widely applied already, few studies have specifically addressed the effect of soil moisture to salt estimation from reflectance (Ben-Dor et al., 2002, 2009; Muller and Décamps, 2001), especially at low and moderately affected areas. As a result, a moisture resistant estimation method is of necessary for early detection and quick monitoring of soil salinity in the large spatial scale, viewing from the large spatial and temporal variations of soil moisture, especially in drylands.

Currently, various analytical methods have been developed to derive soil salinity information from remote sensing data, i.e., from the original simple visual interpretation to recent sophisticated techniques such as spectral unmixing (Dehaan and Taylor, 2003). Multivariate statistical techniques such as Multiple Linear Regression, Polynomial Regression, Principle Component Regression, Partial Least Square Regression (PLSR), Artificial Neural Networks (ANN), Multiple Adaptive Regression Splines (MARS) (Chang et al., 2001; Farifteh et al., 2007; Udelhoven et al., 2003; Volkan Bilgili et al., 2010) and other data mining techniques (Brown et al., 2006), have been applied for interpreting the relationships between soil reflectance spectra and various soil properties including salinity. An alternative approach is to set up relative physically based models to simulate soil spectra from soil properties and such mechanical models can be inversely applied to estimate soil properties.

Following the work of Bach and Mauser (1994), a similar model has been developed in this study to simulate the change of soil spectra with different salt contents. This is a simple application of Beer–Lambert's law, which simulates the salt-affected R (reflectance of soil) from the free-of-salt reflectance by the exponential of the absorption coefficient (fitted) and salt contents (as active thickness). The model was applied to simulate soil spectra under various combinations of soil salts and soil moistures, from which wavelengths that were sensitive to (have high correlations with salt contents) but resisted to soil moistures (uncorrelated with soil moistures) were identified. Then such sensitive wavelengths spectra are used to estimate soil salts inversely.

The main objective of this study, therefore, was to develop a simple absorption model by applying reflectance wavelengths which are sensitive to salt contents but resistant to soil moisture, a main factor controlling soil reflectance, and its inverse estimation to estimate soil salt contents. Specifically, the study aims to: (1) explicitly illustrate the change of soil spectra with respect to salt types and salt concentrations; (2) clarify the effects of soil moisture on soil spectra and consequences for estimating soil salinity; (3) develop a model for quantification and modeling of soil salts under different moisture levels, and (4) identification of moisture-resistant sensitive wavelengths for model inversion. To achieve these objectives, we designed controlled laboratory experiments to reveal the effects of soil salt contents and soil moistures on soil reflectance spectra for three dominant salinity types in the semi-arid and arid areas of Western China. For each experiment, soil salt contents and soil moistures were both set into eight levels and for each combination soil reflectance was taken.

2. Material and methods

2.1. Controlled laboratory experiment

A controlled laboratory experiment was used to investigate the relationships between reflectance spectra and soil salinity and soil water. The experiment had a factorial design with two independent variables (soil salinity and soil moisture content) and spectra as the dependent variable.

Soil samples were collected from a typical inland river basin, the Sanggong River, Western China. The basin has an arid climate with a mean annual precipitation, evaporation, temperature and relative humidity of 187 mm, 1841.9 mm, 6.6 °C, 58%, respectively (Luo et al., 2003). Generally, Loessial and Aeolian soil type (Fluvisols and Arenosols in FAO soil classification) are dominant in this region. Various levels of saline affected soils are dispersed in the fluvial flood plain of the lower reaches. Since previous study revealed that sodium-type salinity dominates in the research area (Pu, 2010), three main sodium types of salt (Na_2SO_4, NaCl, and Na_2CO_3, with 99% purity) were hence used for the experiment to create artificial soil salt levels. Typical non-saline (soil salt content about 0.154%) surface soil in the research area was collected and moved to laboratory (sandy loam with sand of 44.37%, silt of 42.68%, and clay of 12.95%), where it formed the base soil for the controlled experiment. The base soil was air-dried, crushed, and passed through a 2-mm sieve according to Van Reeuwijk (1993) procedure. Physical and chemical properties of the base soil had been previously analyzed with four replicates (Pu, 2010).

Each of the three sodium types of salt was used to artificially create eight levels (percentage by weight) of salt salinity in the base soil: 0, 0.8, 1.6, 2.6, 4, 7, 10, and 20%. The ranges cover from the non-salinity to the heaviest salinity that had ever been reported. For each level of soil salt, eight levels of soil moisture content were designed on relative weight basis as follows: 1.75 (air-dried soils), 5, 7.5, 10, 12.5, 15, 17.5, and 20% (Table 1).

Four replicate dishes were prepared for each of salt-moisture combination. Each dish (7 cm diameter) was initially filled with about 150 g of air-dried base soil with approximately 3 cm depth. 50 ml aqueous salt solutions were prepared by adding distilled water for each salt level using standard methods. The soil samples were irrigated with salt solution before drying them at room temperature to simulate evaporation. The moisture of air-dried samples was estimated to be 1.75% and previous study in the area suggested that the moisture was seldom over 20% (Pu, 2010), the irrigated samples were air-dried for two weeks before adjusting moisture content to between 1.75 and 20% (which was estimated on relative weight basis, and corrected for salt content).

Once the irrigated samples had air-dried, soil reflectance spectra were measured for each sample repeatedly using an Analytical Spectral Device FieldSpec FR (ASD, USA) spectrometer covering wavelengths from 350 to 2500 nm at an interval of 1 nm. Soil samples were illuminated with one tungsten quartz halogen filament lamp, which was placed to one side and 50 cm from the sample with the light beam at