Ecological Indicators 54 (2015) 116–123

Contents lists available at ScienceDirect

Ecological Indicators

journal homepage: www.elsevier.com/locate/ecolind

Developing and applying novel spectral feature parameters for classifying soil salt types in arid land

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ARTICLE INFO

Article history:
Received 27 June 2014
Received in revised form 6 January 2015
Accepted 17 February 2015

Keywords:
Arid land
Soil salinity
Salt type
Hyperspectral
Feature parameter
Classification algorithm

ABSTRACT

Soil salinization is a major desertification process that threatens especially the stability of arid ecosystems. There is an urgent need for intensive monitoring and quick assessment of salinization through remote sensing as a tool for combating desertification in such ecosystems. Recent researches have revealed that in order to retrieve soil salt contents accurately from hyperspectral reflectance, a pre-knowledge of salt types is required, which greatly outlines the spectral features of saline soil reflectance. In this study, a set of feature parameters have been developed after a thorough investigation of spectral responses to different soil salt types and salt contents for quick and accurate classification of soil salt types. The application has been validated using three independent datasets composed from: laboratory experiments (dataset I), *in-situ* field measurements (dataset II), and satellite-borne Hyperion image (dataset III). For comparison, four other common classification algorithms have been validated using the same datasets. The results showed that the new approach proposed in this study performed well with not only single-type but also multiple-type salts for which the four common algorithms performed rather fairly. Furthermore, validating using datasets II and III showed that the newly proposed approach had a stable performance while the other four failed, indicating the advantage of the new approach. The feature parameters developed in this study hence provide a novel and efficient approach for salt type classification from reflectance spectra, and we foresee its potential applications on large-scale soil salt type mapping towards better understanding soil salinity characterization from remote sensing data.

1. Introduction

Soil salinization is one of the most common land degradation processes in arid and semi-arid regions (Richards, 1954; FAO, 1988), where accumulated soluble salts in the soil, influences soil properties and the environment, and hence affecting soil productivity (Mahmoud et al., 2009). Typically, saline soils are highly erosive and have poor structure, low fertility, low microbial activity, and other attributes not conducive for plant growth (Masoud et al., 2006). To enhance sustainable agricultural management in arid and semi-arid environments, timely and proper decisions on combating soil salinization must be achieved through early identification and monitoring of salt-affected areas.

Remote sensing offers a quick and efficient tool for soil salinization identification and monitoring (Wang et al., 2012a). Compared with expensive, time-consuming and intensive sampling requirements of traditional techniques for identifying and monitoring soil salinization, high revisiting frequency and large spatial coverage of remote sensing data offers incomparable advantages on understanding spatiotemporal variations of soil salinity. In the past decade, remote sensing has been used widely to investigate soil salinity (Ben-Dor et al., 2002; Dehaan and Taylor, 2002, 2003; Metternicht and Zinck, 2003; Farifteh et al., 2006, 2008; Mahmoud et al., 2009; Wang et al., 2012a). These ranged from simple visual interpretation of hardcopy satellite images to sophisticated spectral unmixing and multivariate linear and non-linear techniques (Dehaan and Taylor, 2002, 2003; Farifteh et al., 2007).

Despite the existence of numerous studies, application of remote sensing data in salinity studies remains a mounting challenge. In nature, saline soils commonly contain different salt types which greatly affects soil reflectance and may therefore cause

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http://dx.doi.org/10.1016/j.ecolind.2015.02.028
1470-160X/

significant errors during soil salt content estimation (Wang et al., 2012b). Several earlier studies have tried to deal with this dilemma. For instance, based on laboratory control experiments with different salt types and content levels, Howari et al. (2002) reported that different salt types exhibit completely different spectrum curves. Our previous study had shown that the soil spectra of different salt types are very different and even greater than the differences caused by different salt content levels of a single salt type, indicating that accurate retrieval of soil salt content requires prior identifying the salt types (Wang et al., 2012b). However, whether the recent efforts in modeling and classification techniques are able to overcome this limitation and provide a relatively accurate method in salinity studies remains a challenge. Farifteh et al. (2008) tried to identify different soil salt types using two spectral identification algorithms (PIMA and TSG), based on statistical methods identifying an unknown mineral from a reference library, but obtained low accuracy. Although there are a number of algorithms available for classification, they usually require complex statistical processes and very few studies have ever reported success for soil salt type classification.

Parameters of spectral features may offer another approach for soil salt type classification. Feature parameters generally can represent the main feature characteristics of the entire wavelength domain but with high-adaptability to spectral resolution and with high-sensitivity to a given specific property (Kokaly and Clark, 1999). Therefore, use of spectral feature parameters may provide a simple and faster alternative for property-understanding including classification. There are many studies that have used varied spectral feature parameters (in some studies called shape parameters or feature characteristics) in retrieving vegetation and soil properties such as chlorophyll (Baranoski and Rokne, 2005; le Maire et al., 2004), vegetation water content (Curran et al., 2001; Mutanga et al., 2005), environmental stress (Clevers et al., 2004; Kooistra et al., 2004) and so. For soil properties, several attempts have been achieved by use of varied spectral feature parameters (such as the position, depth, width, area). These included soil composition (Van der Meer, 2004; Xu et al., 2008), soil grain size (Ghrefat et al., 2007), soil rubification (Ben-Dor et al., 2006), soil moisture (Demattê et al., 2006; Lobell and Asner, 2002), and soil salinity (Taylor, 2004; Farifteh et al., 2008), but few on soil salt types. Since feature parameters have several advantages on applications, such as their simple forms, their ability to represent the main feature characteristics of entire wavelengths, their high-adaptability to spectral resolution, and their high-sensitivity to specific parameter (Kokaly and Clark, 1999), it is foreseen that they may offer a quick and easy way also on soil salt type classification.

This paper aimed at developing novel spectral feature parameters that are specifically oriented to providing simple and quick classification of soil salt types based on hyperspectral reflected information. Such feature parameters are identified and generalized *via* thorough investigations on reflected spectra collected from soils treated with different salt types and concentrations in laboratory. They are further validated using *in situ* field-measured data (dataset II) and hyperspectral image data obtained by the satellite-borne Hyperion sensor (dataset III). In addition, for comparison, the current commonly applied classification techniques in remote sensing studies, *e.g.* mostly maximum likelihood (Jia and Richards, 1994; Gopinath, 1998), *k*-nearest neighbor (Denœux, 2008; Franco-Lopez et al., 2001), support vector machine (Cortes and Vapnik, 1995; Vapnik, 1998) and artificial neural network (Hammerstrom, 1993; Nurnberger et al., 2002), are applied for classifying soil salt types. All the four techniques have been widely applied in many studies, such as land cover, crops, natural vegetation, soil characteristics (Mucherino et al., 2009) with remote sensing imagery, or hyperspectral measurements etc., but with few studies on soil salt types.

2. Materials and methods

2.1. Laboratory experiment, field sampling, and different datasets

2.1.1. Controlled laboratory experiment (Dataset I)

Spectral data of artificial soils with different soil salt types and salinity were measured in laboratory. Typical non-saline surface soil (soil salt content of ca. 0.154% as determined in laboratory later) from Sanggong River watershed (43°09′45°29″N, 87°47′88°17″E) in Xinjiang, China, was collected and moved to laboratory (see Fig. 1 for the watershed location and sampling strategy). The watershed covers a drainage area of 1670 km^2 and experiences a continental type of climate with an average annual rainfall of 220 mm and an average annual temperature of 6.9 °C (Luo et al., 2003). The alluvial plain in our sampling site has a fine-textured soil (sandy loam with sand of 44.37%, silt of 42.68%, and clay of 12.95%) (Wang et al., 2012a). The soil samples were air-dried, crushed, and passed through a 2-mm sieve to form the base soil for further experiments. Thereafter, the samples were treated with different salts and corresponding spectral data were taken in the laboratory.

The salt minerals mainly responsible for salinity of soil are found within three chemical groups, *i.e.*, carbonates, halides, and sulphates. Therefore, pure NaCl, Na_2CO_3 and Na_2SO_4 in solutions were used to produce three single-type and three salt mixtures (NaCl + Na_2CO_3, NaCl + Na_2SO_4, and Na_2CO_3 + Na_2SO_4) at various salinities. For three single-type salt groups, 7 different levels of salt concentration by weight of dry soil was assigned for each saline soil treatment, which has been replicated three times. While for the three salt mixtures, different proportions of the given two salts were set ranging at 1:9, 3:7, 5:5, 7:3, and 9:1. For each proportion, 5 different levels of soil salt content from 7 g/kg to 200 g/kg were examined with three replicates, resulted in a total of 75 measurements for three composite groups. Reflected spectra were taken using an ASD spectroradiometer covering wavelengths from 350 to 2500 nm (ASD FR, ASD, USA). Detail description of experiments can be found in Wang et al. (2012a).

2.1.2. Field in situ measurements (Dataset II)

The Dataset II composed different salt types, salinity, and other soil properties as well as reflected spectra taken using ASD spectroradiometer *in situ* in field. In total 31 sampled sites were collected in May 2009 inside the watershed across the alluvial plain (oasis) in the low reaches where soil salinization frequently occurs (see Fig. 1 for locations). Each composite sampled site consisted of five subsamples collected within a 90 × 90 m grid, and the position was determined with a GPS unit. After soil reflected spectra were measured *in situ* in the field, the composite topsoil samples were collected and taken to laboratory for analysis of soil chemical and physical properties (including soil moisture, electrical conductivity, pH, concentrations of eight soluble salt ions, and total soluble salt content). Detail description of spectra measurements and soil sampling can also be found in Pu (2010) and Wang et al. (2012a).

2.1.3. Satellite-born data (Dataset III)

An additional dataset retrieved from a Hyperion image dated on May 12, 2009 covering the sampling area as well as within the period of field measurements was compiled for further analysis. Hyperion image was processed through various procedures as detailed in Pu (2010) before being used to retrieve satellite-borne hyperspectral reflectance for each sampled sites. Procedures included destriping, smile effect correction, atmospheric correction, as well as geometrical correction (Goodenough et al., 2003; Kruse et al., 2003). Atmospheric correction was based on the FLAASH module inside ENVI software. Geometrical correction has been based on a geo-referenced TM scene using 16 ground control points (GCPs) and obtained an RMSE of 0.44 m. Satellite-borne