



# New methods for improving the remote sensing estimation of soil organic matter content (SOMC) in the Ebinur Lake Wetland National Nature Reserve (ELWNNR) in northwest China

Xiaoping Wang<sup>a,b</sup>, Fei Zhang<sup>a,b,c,\*</sup>, Hsiang-te Kung<sup>d</sup>, Verner Carl Johnson<sup>e</sup>

<sup>a</sup> Key Laboratory of Smart City and Environmental Modeling of Higher Education Institute, College of Resources and Environment Sciences, Xinjiang University, Urumqi 830046, PR China

<sup>b</sup> Key Laboratory of Oasis Ecology, Xinjiang University, Urumqi 830046, Xinjiang, PR China

<sup>c</sup> Engineering Research Center of Central Asia Geoinformation Development and Utilization, National Administration of Surveying, Mapping and Geoinformation, Urumqi 830002, PR China

<sup>d</sup> Department of Earth Sciences, University of Memphis, Memphis, TN 38152, USA

<sup>e</sup> Department of Physical and Environmental Sciences, Colorado Mesa University, Grand Junction, CO 81501, USA

## ARTICLE INFO

### Keywords:

Soil organic matter  
Spectrum analysis  
Fractional order derivatives  
Remote sensing index  
Subsection of spectral band method

## ABSTRACT

This study aimed to improve the potential of Analytical Spectral Devices (ASD) hyperspectral and Landsat Operational Land Imager (OLI) data in predicting soil organic matter content (SOMC) in the bare topsoil of the Ebinur Lake Wetland National Nature Reserve (ELWNNR) in northwest China. The results indicated that the correlation of coefficients (R) between SOMCs and hyperspectral data processed by fractional derivative were significant at the 0.01 level; the number of wave bands increased initially and then decreased when the order increased. The correlation of coefficient peak appeared at the 1.2 order with a value of 0.52. The correlation of coefficients (R) between SOMCs and the optimal remote sensing indexes (the ratio index, RI; difference index, DI; and the normalized difference index, NDI) of peaked at the 1.2 order, with correlation of coefficients (R) values of 0.81, 0.86 and 0.82, respectively. Six SOMC estimation models were created by means of a single band and optimal remote sensing indexes using Gray Relational Analysis-BP Neural Network (GRA-BPNN). This study found that the optimal model was a 1.2 order derivative model, where the lowest root mean square error (RMSE) was 3.26 g/kg, the highest was 0.92, and the residual prediction deviation (RPD) was 2.26. To complete the high accuracy retrieval of SOMCs, based on Landsat OLI operational land images data, more ‘hidden’ information from the Landsat OLI images were obtained by employing the subsection of spectral band method and the fractional derivative algorithm. Accuracy of the SOMC map was attained by the optimal model of the ground hyperspectral data and the Landsat OLI data, which had low RMSE values of 4.21 g/kg and 4.16 g/kg, respectively. Therefore, we conclude that the SOMC can be estimated and retrieved using a fractional derivative algorithm, the subsection of spectral band method, and the optimal remote sensing index.

## 1. Introduction

Soil organic matter content (SOMC) is a critical property in soil nutrients. It supports plant growth (Seely et al., 2010; Six and Paustian, 2014; Castaldi et al., 2016; Jin et al., 2016) and plays an important role in soil formation, soil fertility, environmental protection, and the sustainable development of agriculture and forestry (Nocita et al., 2015). Therefore, SOMC is an effective evaluation index for soil fertility. Conventional SOMC estimation has relied solely on ground samples and laboratory analyses. This method is highly accurate, but is slow, costly,

destructive and spatially limited; therefore, it is not suitable for efficient monitoring of SOMC.

Recently, remote sensing methods have been applied to estimate SOMC as visible and near infrared reflectance (Vis-NIR) spectroscopy is a physical non-destructive, rapid, reproducible method that provides inexpensive prediction of soil physical, chemical and biological properties (Ben-Dor and Banin, 1995; Ben-Dor et al., 2002). Reflectance signals are produced by vibrations in bonds between C, N, H, O, P, and S atoms. Weak overtones and combinations of fundamental vibrations due to the stretching and bending of NH, OH and CH groups dominate

\* Corresponding author at: Key Laboratory of Smart City and Environmental Modeling of Higher Education Institute, College of Resources and Environment Sciences, Xinjiang University, Urumqi 830046, PR China.

E-mail address: [zhangfei3s@xju.edu.cn](mailto:zhangfei3s@xju.edu.cn) (F. Zhang).

<https://doi.org/10.1016/j.rse.2018.09.020>

Received 23 January 2018; Received in revised form 19 September 2018; Accepted 22 September 2018

0034-4257/ © 2018 Elsevier Inc. All rights reserved.

the NIR (700–2500 nm) and electronic transitions the visible (400–700 nm) portions of the electromagnetic (EM) spectrum (Ben-Dor et al., 1999). Remote sensing technology plays a key role in global and regional SOMC monitoring. Many scholars (e.g., Chang and Laird, 2002; Bartholomeus et al., 2008; Barthès et al., 2006; Viscarra Rossel et al., 2010; Cécillon et al., 2009; Franceschini et al., 2015; Vaudour et al., 2016) have reported the benefits of the visible and mid-infrared spectrum for the shorter cycle and lower cost in estimation of SOMC compared to conventional SOMC analyses, which could enable significant reductions or hyperspectral remote sensing alternatives that could complement traditional methods for monitoring SOMC (Luce et al., 2014; Stenborg and Demattê, 2015; Jin et al., 2015; Eisele et al., 2015). Other studies used multispectral remote sensing data, including IKONOS, SPOT, Hyperion hyperspectral data, Landsat TM and LiDAR data aiming at improving the accuracy of predicting the parameters of land surfaces at the regional scale (Castaldi et al., 2016; Vaudour et al., 2016; Peón et al., 2017; Rasel, 2017). Although with the development of spaceborne, airborne multispectral and hyperspectral technologies, remote sensing data have been gradually applied to the estimation of SOMC (Gomez et al., 2008; Jing et al., 2010). These studies only used spectral data from the remote sensing data. However, the estimation of SOMC is to be realized by establishing the relationship between original data and SOMC. In processing, remote sensing data are affected by many environmental factors, such as noise that occur in the raw data. Previous studies using atmospheric correction method in data processing reduced the noise in the process of atmospheric transmission, but ignored other noises. Hence, it is required to explore new ways to minimum noise data and to improve the accuracy in SOMC estimation.

The derivative spectrum is a powerful remote sensing processing tool that extracts more sensitive spectral information than raw data (Wiggins et al., 2007). The first derivative (FD) and the second derivative (SD) are methods of mathematical change. The first derivative (FD) represents the slope of the spectral curve, and the second derivative (SD) represents the curvature of the spectral curve (Holden and LeDrew, 2008; Pu et al., 2008; Wang et al., 2018). Derivative techniques of remote sensing data have been widely applied to reduce noise, decrease the baseline effects, solve overlapping problems, sharpen the spectral features, capture subtle details of spectral curves, and improve the extracted accuracy of land surface parameters (Stavroulakis et al., 2013; Tsai and Philpot, 2002). Numerous studies using hyperspectral remote sensing concentrated on the untreated spectral or integer derivatives methods (i.e., FD and SD) of remote sensing data, but ignored fractional derivative methods.

However, FD and SD have some disadvantages. Many studies have shown that the spectroscopy processing methods of FD and SD have led to spectral information loss or noise amplification (Kharintsev and Salakhov, 2015). Therefore, fractional derivatives complement the FD and SD methods and provide a new solution in processing remote sensing data. Fractional derivatives are similar to integer ordering, but the order is arbitrarily extended (Li et al., 2015). There are some cases in the processing of remote sensing data where fractional derivatives were used. Schmitt (1998) introduced the fractional derivative method in the analysis of diffuse-reflectance spectra. J.Z. Wang et al. (2016) estimated desert soil organic carbon content based on hyperspectral data that was preprocessed with a fractional derivative.

We selected the Ebinur Lake Wetland National Nature Reserve (ELWNNR) in Xinjiang, China, near the Kazakhstan border (Fig. 1a) as the study area. The purposes of this study are (1) extracting more 'hidden' information from remote sensing data using a subsection of spectral band method and a fractional derivative algorithm, (2) analyzing the relationship between remote sensing data processed by a fractional order derivative and SOMC, (3) building and discussing the variation tendencies of some parameters in the GRA-BPNN models, and (4) retrieving SOMC based on optimal GRA-BPNN models in the ELWNNR.

## 2. Materials and methods

### 2.1. Study area

The ELWNNR is located in the northwest of Xinjiang Uygur Autonomous Province at 44°54'–45°08'N and 82°35'–83°10'E (Fig. 1). Ebinur Lake, the largest saltwater lake in Xinjiang, is in the geologic structural basin formed from the faults, created by the Himalayan Orogeny, when India merged with Asia that began 45 million years ago. The soil types in the study area are mainly desert soil made up of piedmont psephitic, salt and gypsum. Overall, the study area contains vast areas of dry lake beds abundant in salt-rich loose sediments. The total coverage of the ELWNNR is 2670.8 km<sup>2</sup>. ELWNNR contains a variety of land types, such as water body, vegetation, wetland, desert, salinized land, and others (i.e., Gobi and mountains) in terms of land use and land cover. The climate in The ELWNNR is a continental arid, with hot summers, cold winters, rare precipitation, and intense evaporation. All these events lead to dust storms in winter. Vegetation is scarce and the ecological environment deteriorates substantially. Therefore, the increase in vegetation coverage is one of the important projects for ecological restoration in the ELWNNR (Zhang et al., 2015; Yu et al., 2017; Wang et al., 2017).

### 2.2. Data collection

#### 2.2.1. Soil sample collection

Five topsoil samples at 0–20 cm (30 × 30 m square in Fig. 1e) to represent each of the 45 soil sites were collected in the field from May 17th to May 25th and again from August 7th to August 15th, 2016 (see sample location map in Fig. 1c). The sample sites were selected according to the soil types and surface heterogeneity, including consideration for the diversity of soil surface characteristics. The samples were collected in several trips using interval sampling method such as shoveling and tape measure. The main designed route of experimental sampling point was along the lake, with 5 km intervals in between. Open and flat areas were selected as sample sites. A portable global positioning system (GPS, G350, UniStrong, China) unit was employed to provide location and time information of each sample collected. Each soil sample (approximately 2 kg) was put into a plastic bag, labeled, sealed, and transported to the laboratory. They then were naturally air-dried and sieved through a 2-mm sieve to remove stones, weed roots, and other impurities (O'Kelly, 2004). Soil organic carbon content (SOCC) was measured using the K<sub>2</sub>Cr<sub>2</sub>O<sub>7</sub>–H<sub>2</sub>SO<sub>4</sub> oxidation method. A conversion factor of 1.724 is commonly used to convert SOCC to SOMC: SOMC (%) = SOCC (%) × 1.724 (Jin et al., 2016).

#### 2.2.2. Spectral measurements

A USA Analytical Spectral Devices (ASD) FieldSpec® 3 Portable Spectrometer (Analytical Spectral Devices, Boulder, CO, USA), spectral ranging 350–2500 nm with 2151 output bands, was used to collect the hyperspectral readings of soil in a dark laboratory. Two 90 W tungsten halogen bulbs were used as light sources. On the opposite sides of the soil sample a zenith angle was set at 30°. Soil samples were placed in a container with a diameter of 10 cm and a depth of 1.5 cm, and were flattened at the surface. The probe field of view was set at 15°, and the distance from the ground was set as approximately 6 cm. A standardized white panel was employed to calibrate reflectance spectra of the soil. Ten spectra for each soil sample were collected, and the actual reflectance spectra of the soil samples were obtained by using the ViewSpec Pro (Analytical Spectral Devices, Boulder, CO, USA. Version 2.14).

#### 2.2.3. Landsat OLI data acquisition and preprocessing

Cloud-free Landsat OLIs (operational land images) were used in this study. Landsat OLI data were obtained from the USGS (<http://glovis.usgs.gov/>) close to the date when the soil samples were collected (May

Download English Version:

<https://daneshyari.com/en/article/11025034>

Download Persian Version:

<https://daneshyari.com/article/11025034>

[Daneshyari.com](https://daneshyari.com)