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Simulating spatial distribution of coastal soil carbon content using a comprehensive land surface factor system based on remote sensing

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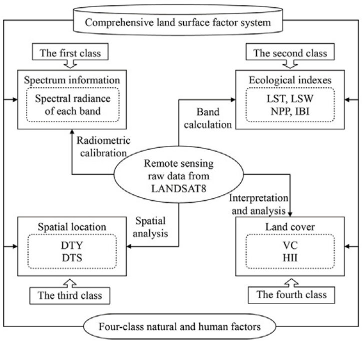
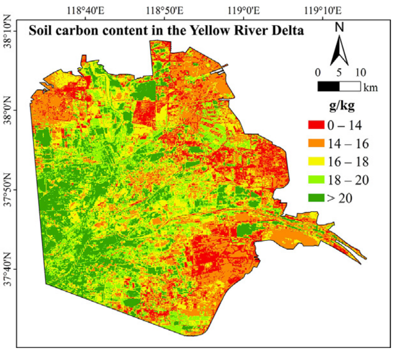
HIGHLIGHTS

- A comprehensive land surface factor system for soil carbon simulation was proposed.
- The system utilized the ecological significances of remote sensing data.
- Different algorithms were used to conduct soil carbon simulation in Yellow River Delta.
- The system was proven to have low uncertainty, high accuracy and good applicability.

GRAPHICAL ABSTRACT





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ABSTRACT

Surface soil carbon content (SCC) in coastal area is affected by complex factors, and revealing the SCC spatial distribution is considerably significant for judging the quantity of stored carbon and identifying the driving factors of SCC variation. A comprehensive land surface factor system (CLSFS) was established; it utilized the ecological significances of remote sensing data and included four-class factors, namely, spectrum information, ecological indices, spatial location, and land cover. Different simulation algorithms, including single-factor regression (SFR), multiple-factor regression (MFR), partial least squares regression (PLSR), and back propagation neural network (BPNN), were adopted to conduct the surface (0–30 cm) SCC mapping in the Yellow River Delta in China, and a 10-fold cross validation approach was used to validate the uncertainty and accuracy of the algorithms. The results indicated that the mean simulated standard deviations were all <0.5 g/kg and thus showed a low uncertainty; the mean root mean squared errors based on the simulated and measured SCC were 3.88 g/kg (SFR), 3.85 g/kg (PLSR), 3.67 g/kg (MFR), and 2.78 g/kg (BPNN) with the BPNN exhibiting a high accuracy compared to similar studies. The mean SCC was 17.40 g/kg in the Yellow River Delta with distinct spatial heterogeneity; in general, the SCC in the alongshore regions, except for estuaries, was low, and that in the west of the study area was high. The mean SCCs in farmland (18.31 g/kg) and wetland vegetation (17.98 g/kg) were higher than those in water area (16.07 g/kg), saltern (15.61 g/kg), and bare land (14.71 g/kg). Land-sea interaction and human activity jointly affected the SCC spatial distribution. The CLSFS was proven to have good applicability, and can be widely used in simulating the SCC spatial distribution in coastal areas.

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1. Introduction

As one of the largest carbon pools in the natural ecosystem, soil carbon pool is of great significance for global climate change and carbon cycling (Eswaran et al., 1993; Batjes, 1996; Lal, 2002). Coastal area is the key region for carbon sink; coastal vegetations, such as mangroves, salt marshes, and seagrasses, play a critical role in global carbon sequestration, and the carbon sequestered by these vegetations is termed "blue carbon" (Mcleod et al., 2011; Pendleton et al., 2012; Duarte et al., 2013). The improvement of blue carbon is important for increasing carbon sink. The coastal soil is the final carrier for the carbon and a stable pool for carbon storage, which indicates the long-term scale of carbon sequestration (Mcleod et al., 2011; Chi et al., 2017a). Revealing the spatial characteristics and influencing factors of coastal soil carbon content (SCC) is considerably significant for judging the quantity of stored carbon, identifying the driving factors of SCC variation, and providing reference for human activity regulation. SCC is a balanced result of carbon capture and decomposition and affected by complex factors (Post et al., 2001). Surface (0–30 cm) SCC is the primary component of the SCC in the whole soil layer (Jia et al., 2017); it is influenced by not only strong land–sea interaction in coastal area, including substantial sediment input, coastal erosion, and seawater intrusion, but also increasing human activities, consisting of human interference (e.g., coastal reclamation, vegetation occupation, pollutant emission) and human regulation (e.g., nature reserve construction and ecological restoration) (Shabman and Batie, 1978; Selman et al., 2008; Xiong et al., 2014). All aforementioned factors directly or indirectly exhibit on land surface and thus result in the peculiarity of land cover types and distinct spatial heterogeneity of SCC.

The study on SCC spatial distribution has been focused for a long time, yet was ever limited to the great difficulty and high cost of field investigation. The developments of remote sensing and geographic information system have provided a convenient and economical way for SCC mapping (Pulliainen et al., 2001; Croft et al., 2012). The initially used methods are spatial interpolation (Yu et al., 2012; Qiu et al., 2013), as well as simulation based on land cover types (Wang et al., 2002). These methods are simple to use, whereas possess a low accuracy due to the neglect of land surface characteristics. Many researches were conducted using the raw spectra; regression analysis was adopted to establish the relationships between the spectra and measured SCC; and then the SCC spatial distributions were simulated based on the relationships (Kissel and Chen, 2005; Gomez et al., 2008; Ladoni et al., 2010; Katsuhisa et al., 2011). However, the raw spectra are not designed with distinct ecological purposes, and thus the simulation accuracy is limited. Lately, many scholars began to process the remote sensing data through band calculation, and various vegetation indices, including normalized difference vegetation index, enhanced vegetation index, biomass index, etc., and terrain indices, including altitude, slope, aspect, hill index, etc., were obtained and tested to be closely correlated with SCC (Clough and Green, 2013; Ließ et al., 2016; Rasel, 2017). The simulation models were established based on these indices and good performances were achieved in some specific regions. Nevertheless, only these indices still could not adequately represent the complex factors influencing SCC in coastal areas with obvious spatial heterogeneity of land surface features. Then, the multiple factors of SCC have been paid attentions to; climate factors, parent material, soil types, hydrology, and land use were collected as the predictors (Akpa et al., 2016; Kim and Grunwald, 2016; Grinand et al., 2017; Schillaci et al., 2017a, 2017b; Yang et al., 2017; Zhang et al., 2017; Wang et al., 2018). Meanwhile, in-situ measurement of spectra, such as visible and near-infrared, mid-infrared, and gamma-ray, were also conducted and high simulation accuracies were achieved (Viscarra Rossel and Behrens, 2010; Peng et al., 2015; Priori et al., 2016; Jia et al., 2017). However, the applicability of these methods is limited due to their requirements of field investigation and historical data.

Despite the plentiful achievements of SCC mapping in present studies, the applicability and accuracy of the methods are always antagonistic in many cases. The deficiencies in the high performance and balance of applicability and accuracy are the main limiting factors for the SCC mapping, especially in coastal areas with complex land surface features and high field investigation cost. Meanwhile, the ecological significances of remote sensing data could be further studied. In this study, we established a comprehensive land surface factor system (CLSFS), which utilizes the ecological significances of remote sensing data and includes four-class factors, namely, spectrum information, ecological indices, spatial location, and land cover. Different simulation algorithms, including single-factor regression (SFR), multiple-factor regression (MFR), partial least squares regression (PLSR), and back propagation neural network (BPNN), were then adopted to conduct the SCC mapping using the CLSFS. A 10-fold cross validation approach was conducted to validate the uncertainty of the algorithms; the accuracy of simulation results was tested by using root mean squared error (RMSE), mean absolute error (MAE), and coefficients of determination (R^2) based on the simulated and measured SCC values; the applicability of the CLSFS method was discussed from the aspects of the accessibility of needed data and operability of the simulation process. Then, soil carbon density (SCD) and carbon storage were also calculated based on the SCC results and bulk density to further reveal the spatial characteristics of carbon storage. The study aims to provide a new method with high accuracy and applicability for the SCC simulation in coastal areas and reveal the spatial characteristics and influencing factors of SCC.

2. Materials and methods

2.1. Study area

The Yellow River Delta is the largest newly formed coastal wetland in North China with a large amount of sediment input and unique climate condition (Cui and Li, 2011). It is located south to Bohai Bay and west to Laizhou Bay, which are found in Bohai Sea (Fig. 1). It is covered with various wetland vegetations and provides an important habitat for rare and endangered bird species, but exhibits evident vulnerabilities (Kong et al., 2015). The modern Yellow River Delta was formed since 1934 and is facing severe land–sea change and fast ecosystem evolution due to the comprehensive effects of natural and human factors (Tian et al., 2003; Cui and Li, 2011). The estuary continues to extend to the sea and new wetland is formed due to the sediment input via the Yellow River; other alongshore regions shrink under the effect of coastal erosion (Cui and Li, 2011; Chi et al., 2017a). Meanwhile, human activity has been intensified and expanded in recent decades; it significantly alters the shoreline and influences the land cover types inside the delta, resulting in the great increase in farmland, saltern, and buildings; and farmland has been the largest land cover type in the Yellow River Delta (Xing et al., 2016; Chi et al., 2017a). Some scholars have conducted SCC spatial simulations in the Yellow River Delta; Wang et al. (2002) simulated the SCC spatial distribution based on the extents and mean SCC values of different land cover types; Yu et al. (2012) simulated the SCC through spatial interpolation based on the positions of sampling sites. They have made contributions to revealing the SCC spatial distributions, yet the spatial resolutions of their results were low due to the little consideration on the complex land surface characteristics. The CLSFS involves various natural and human factors, and can represent the spatial heterogeneity of land surface characteristics. Therefore, we used the CLSFS to simulate the surface (0–30 cm) SCC spatial distribution with a resolution of 100 m × 100 m in the Yellow River, and identified the main SCC influencing factors.

On the basis of the modern Yellow River Delta and considering geographical integrity, the scope of the study area was determined using Yuwa Village as the zenith and Tiaohe Estuary and Hongguang fishing port as the endpoints, and the area sums to 2414 km^2 (Fig. 2). The study area is located in Dongying City, Shandong Province, China and