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Developing pedotransfer functions to estimate the S-index for indicating soil quality

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ABSTRACT

Indicating soil quality usually requires many soil properties of which the measurements are time consuming. Therefore, it is desirable to developing simple and effective indices for reflecting soil quality based on soil properties that can be readily obtained. The soil physical quality index, S-index, derived from the slope at the inflection point of the water retention curve (particularly the Van-Genuchten equation), is a comprehensive index for indicating soil properties. By comparing the S-index with a widely used soil quality index (SQI), this study used 298 samples to determine soil chemical and physical properties for calculating SQI, and found that the correlation coefficient between the S-index and SQI was 0.88, indicating that the S-index can represent soil quality well. An artificial neural network (ANN) model and a linear regression (LR) model were proposed for estimating S-index. Results showed that the ANN model was better than LR model in estimating S-index. Particularly, the ANN model with the soil bulk density and soil organic carbon (scenario A1) as inputs, had the highest R^2 of 0.807, while the LR model get the highest R^2 (predicted v.s. observed) of 0.75 with the combination of soil organic carbon, soil bulk density, total nitrogen and available nitrogen. This study is helpful for extending the applications of S-index.

1. Introduction

Soil quality, which is considered as a critical indicator for evaluating land degradation or amelioration, and identifying management practices for sustainable land use, has garnered considerable concerns (Dexter, 2004; Reynolds et al., 2009; Li et al., 2011). Currently, the common soil quality indicator is the soil quality index (SQI) (Andrews and Carroll, 2001). The SQI usually requires many soil physical and chemical properties as inputs, such as the bulk density, soil organic carbon, soil nitrogen, phosphorus and potassium (Andrews and Carroll, 2001). For example, Xie et al. (2015) developed the SQI for reflecting karst rocky desertification, by using total organic carbon, total nitrogen, available phosphorus, microbial biomass carbon and microbial biomass nitrogen; Ngo-Mbogba et al. (2015) developed the SQI by combining some physicochemical properties, such as soil organic matter, available phosphorus, calcium and pH; Askari and Holden (2014) used the soil organic carbon, bulk density and CN (the ratio between carbon and nitrogen) as inputs; and Armenise et al. (2013) developed a weighted-additive SQI for evaluating the effectiveness of different managements on soil quality based on 18 soil physicochemical properties.

Indeed, the soil quality contains three aspects, the physical, chemical and biological quality. However, the soil physical quality is the basement for soil chemical and biological processes, and thus has become topical issues for better studying soil quality (Li et al., 2011). There are many indicators for indicating soil physical quality, including the plant available water capacity, macro porosity, bulk density, organic carbon content, infiltration properties, soil texture, and so forth (Reynolds et al., 2007; Reynolds et al., 2009). Generally, soil physical quality is hard to be directly quantified by some methods or indicators (Dexter and Czyż, 2000), but can be indicated by analyzing a list of soil properties (Moebius et al., 2007; Reynolds et al., 2008).

However, measuring such soil properties are costing and time-consuming. Dexter (2004) proposed a comprehensive index (S-index) for representing soil physical quality, which is derived from the slope of the water retention curve at the inflection point based on the estimated Van-Genuchten equation. The effectiveness of S-index in reflecting critical soil physical functions (properties) has been demonstrated in many studies (Dexter and Czyż, 2007; Keller et al., 2007). For instance,

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Li et al. (2011) found that the S-index was negatively and significantly correlated with soil tensile strength (R^2 = 0.85), and positively correlated with soil organic carbon (R^2 = 0.83); and Naderi-Boldaji and Keller (2016) pointed out a strong positive correlation between compactness degree and reciprocal of S-index (1/S-index) (R^2 = 0.95).

In general, calculation of S-index needs four parameters, the saturated water content (θ_s), residual water content (θ_r), adjustable parameters (m, n) of the Van-Genuchten equation (Van Genuchten, 1980). These four parameters can be reduced to three if using the constraint $m = 1\text{-}1/n$ (Mualem, 1976). Additionally, the θ_r is usually set to be zero, especially in the soils with large fraction of clay (Groenevelt and Grant, 2001; Lassabatere et al., 2006; Dexter et al., 2008). Therefore, at least two parameters need to be determined. Nevertheless, it is still inconvenient to determine the water retention curve for each soil sample to acquire parameter n. For convenience, researchers have developed some empirical models for estimating n (Lassabatere et al., 2006; Minasny and McBratney, 2007). For example, the physical-based models requiring detailed particle size distribution data and porosity (Lassabatere et al., 2006; Xu et al., 2009; Yang et al., 2016), and the neural network based models which requires soil clay and sand content (Minasny and McBratney, 2007; Bagarello and Iovino, 2012). However, measuring soil particle size distribution (at least five fractions) is still time consuming and is unsuitable for rapidly handling large amount of samples. Thus, direct estimation of S-index with minimum input variables may be more attractive in studying soil quality.

This study aimed to test whether the S-index is well related with soil quality index (particularly with soil chemical quality) and develop two pedotransfer functions (models) for estimating S-index with soil properties that can be easily obtained.

2. Materials and methods

2.1. Study area

The study area is located at three sites (Mulian vaillage, Guzhou village, and Mulun reserve (a natural reserve area)) in Huanjiang county, Guangxi province, southwest China (24°44′–25°33′N, 107°51′–108°43′E) (Fig. 1). This area belongs to a subtropical climate with long term mean annual temperature of 18.5 °C and annual precipitation of 1389 mm year^{-1} (Nie et al., 2011). The landform is typical peak-cluster karst landscape with depression and valleys. The main soil type is calcareous soil developed from limestone (Yang et al., 2016).

2.2. Sampling and measuring soil properties

From October 2013 to June 2014, 298 Beerkan infiltration experiments using single ring infiltrometer method (Xu et al., 2012; Yang et al., 2016; Yang et al., 2017) were conducted in land with different vegetation restoration types in Mulian, Guzhou and Mulun. In particular, ecological restoration (from cropland) was started in 2003 and 2007 in Mulian and Guzhou, respectively. The main vegetation types are zenia insignis, toona sinensis, loquat, cirtus, pear, peach, napiergrass and natural restoration shrubland in Mulian and Guzhou (Yang et al., 2017). In order to distinguish vegetation and restoration time, these sampling sites were divided to eight vegetation types, which were the artificial woodland (GAW), cultivated land (GC), natural restoration shrubland (GNRS) in Guzhou (since 2003), artificial grassland (MAG), artificial woodland (MAW), cultivated land (MC), natural restoration shrubland (MNRS) in Mulian and natural reserve (NR) in Mulun.

At each experimental sites, two samples were collected using cutting ring (100 cm^3). One of the samples was used to determine bulk density (BD) through oven drying at 105 °C for 24 h. The other was air-dried and sieved (2 mm) for measuring soil physicochemical properties. Particularly, the soil particle size was determined using the Laser Particle Size Instrument of Mastersizer-2000 (British Malvern Instruments Ltd). The saturated soil moisture content was determined by drying soil samples in an oven at 105 °C for 24 h. Soil chemical properties, including soil organic carbon (SOC), total nitrogen (TN), total phosphorus (TP), total potassium (TK), available nitrogen (AN), available phosphorus (AP) and available potassium (AK), were determined in the laboratory. Table 1 showed the methods of determining these properties.

2.3. S-index and soil quality index

The S-index (SI) for each sites derived from the soil water retention curve (Dexter, 2004), which is plotted with the log-transformed soil suction (ln(h)) against gravimetric soil water content:

$$\theta = (\theta_s - \theta_r)[1 + (\alpha * h)^n]^{-m} + \theta_r \quad (1)$$

where θ_s is the measured saturated soil water content (kg kg^{-1}), θ_r is the residual soil water content (kg kg^{-1}), h is the water suction (cm); and m, n and α are the adjustable parameters of Van-Genuchten equation ($m = 1\text{-}1/n$). With Eq. (1), the S-index value corresponded to the slope at the inflection point:

$$SI = -n(\theta_s - \theta_r)\left[1 + \frac{1}{m}\right]^{-1-m} \quad (2)$$

$$\theta_i = (\theta_s - \theta_r)[1 + 1/\text{m}]^{-m} + \theta_r \quad (3)$$

$$h_i = \frac{1}{\alpha}\left[\frac{1}{m}\right]^{1/n} \quad (4)$$

where the θ_i and h_i are the water content and water suction at the inflection point, respectively.

The soil quality index (SQI) was derived from the calculation based on the equation from Xie et al. (2015) using the properties of SOC, TN, TP, TK, AN, AP, AK and BD. In order to eliminate the scales of these indicators, these variables are standardized using Eq. (5) firstly:

$$X = \frac{x_i - x_{min}}{x_{max} - x_{min}} \quad (5)$$

where X represents standardized value; x_i, $x_{\min}$, $x_{\max}$ represents the original, minimum and maximum value of the soil chemical properties, respectively. Then, the principal component analysis (PCA) method was employed to reduce the dimension for obtaining a minimum dataset (Andrews et al., 2002; Armenise et al., 2013) and avoiding information redundancy. The SQI was calculated according to Eq. (6):

$$SQI = \sum_{k=1}^{p} (V_k * P_{ki}) \quad (6)$$

Where the V_k represents the variance contribution rate for the k (k = 1, 2, 3 … p) principle components; and P_{ki} represents the principal component score and i is the number of samples.

2.4. Developments of pedotransfer functions

Currently, the artificial neural network (ANN) method is popular in regression analysis. The good performance of ANN model in some situations benefits from the learning mechanism, when the relationship between dependent and independent variables are unknown (Chang and Islam, 2000). Moreover, the ANN model has the adaptive ability to the dynamic changes from the original environment (Sun, 2013). Compared to the traditional regression method, the ignorance of a priori knowlede of model concept is one of the advantanges of the artificial neural network model (Schaap et al., 1998). The ANN model in this study is based on the Levenberg-Marquardt algorithm (Marquardt, 1963). This algorithm minimizes the objective function:

$$O(t, t') = \sum_{i=1}^{N1} \sum_{j=1}^{N2} (t_{i,j} - t'_{i,j})^2 \quad (7)$$

where the t and t' are the observed and estimated variables, $N1$ and $N2$