QUANTITATIVE MAPPING OF SOIL ORGANIC MATERIAL USING FIELD SPECTROMETER AND HYPERSPECTRAL REMOTE SENSING

Zhuo Luo[a], Liu Yaolin*[a], Wu Jian[a], Wang Jing[b]

[a]School of Resource and Environmental Science, Wuhan University, Wuhan, 430079, China;
[b]Key Laboratory of Land Use, Ministry of Land and Resources, Beijing, 100035
China-(yaolin610)@163.com

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ABSTRACT:

Mapping and dating soil organic material is of great importance in soil use and evaluation. Yet the most common mapping method of these features is based on visual, qualitative interpretation of air-photos. In this study we examine the feasibility of mapping soil organic material content by using airborne hyperspectral reflective remote sensing methodology. This technique was tested in Henshan County located in north of Shanxi province. A correlation analysis was performed between soil organic material data and color indices (brightness index, coloration index, hue index, redness index and saturation index). Using these correlations we were able to build up the regression model, and map the soil organic material content by calculating each pixel of Hyperion image. The accuracy assessment (the overall accuracy estimated as 76%) showed that the map is reliable and significantly correlated with known stabilization processes throughout the study area. The quantitative methodology developed in this study for mapping soil organic material can be adapted to other arid regions throughout the world.

1. INTRODUCTION

Remote sensing of soils plays a major role in both soil survey and soil mapping applications. The development of methods to map soil properties using optical remote sensing data in combination with field measurements has been the objective of several studies during the last decade [1]~[3]. Organic matter is a macronutrient essential to plants, but one of the most deficient soil nutrients in terrestrial ecosystems. Continuous cropping or decreasing the frequency of summer fallow (F) in cereal-based dryland rotations may have benefits other than greater water utilization and erosion control. We hypothesized that rotations with no fallow or minimum fallow frequency can produce more biomass and cover than the traditional winter wheat (Triticum aestivum L.)-summer fallow systems (W-F), and ultimately, greater amounts of soil organic matter (SOM) [4]. Accordingly, Mapping and dating soil organic matter is vital to precise agriculture and soil evaluation. However, traditional remote sensing data seems not to be well adopted for mapping soil organic matter. Firstly, diagnostic features of soil nitrogen are generally weak because of poor content. Secondly, mapping of soil organic matter is relative difficult because many other soil chemical and physical properties (e.g., moisture, surface roughness, nitrogen) also influence soil reflectance [5]. Finally, from a remote platform the recorded reflectance is often the (mixed) result of several surface components (i.e., mixed pixel problem) [3], and at the same time atmospheric scattering and absorption processes mask soil diagnostic features [6]. Imaging Spectrometry (IS) or hyperspectral technology, as an advanced tool that provides high spectral resolution data (near-laboratory-quality reflectance and emittance data) for each single picture element (pixel) from a far distance [7], significantly broadens the utility for further mapping of the soil surface from a more precise chemical and physical point of view [8]. With the development of hyperspectral sensors, spectral features related to characteristic absorption bands of soil organic matter can be mapped with more detail [9]. A reasonable agreement was obtained between the two data sets (laboratory and air) suggesting that infiltration rates values can be estimated remotely. It is strongly suggested that future study, will use the full optical range (VIS-NIR-SWIR-TIR) in the IS technology to map the crust status in a better precise way. [10] Therefore, remote sensing of soils by high spectral resolution sensors is receiving more and more attention to rapidly and quantitatively map soils from far distances [11]~[12].

Many remote sensing methods were studied to map soil organic matter in the past decades. Dalai et al. [13] predicted the soil moisture, soil organic material and soil nitrogen in Australia using NIR spectral method. Uno, Y. [14] predicted that the high prediction accuracy obtained (NRMSE = 9.98% for PCA-SMLR; 12.08% for PCA-ANN models) suggests that hyperspecral remote sensing can be an effective tool in describing the variability of soil organic matter (SOM) on a field scale. Bonifazi, Giuseppe. [15] examined the possibility offered by multi and hyperspectral digital imaging based spectrophotometric techniques in order to perform fast, reliable and low cost "in situ" analyses to identify and quantify specific soil attributes, of primary importance in agriculture, as: water, basic nutrients and organic matter content. Bajwa, S.G. [16]

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showed that soil fertility factors important for precision agriculture applications can be successfully modeled on hyperspectral visible/infrared (VIR) remote sensing data with partial least square regression models.

This study was designed to evaluate the potential of spectral analysis of hyperspectrally reflective data as an approach for mapping soil organic matter content in arid regions. In order to Quantitative mapping the soil organic matter, The 220-channel Hyperion data of 30m spatial resolution was chosen. Ultimately, the regression model was built up to process the Hyperion image to visualize the spatial distribution of soil organic matter content.

2. DATA

2.1 Study area

The study area is in Henshan county in northern Shanxi province, China (latitude from 37°22′ to 38°74 north and longitude from 108°65′ to 110°02′ east)(Fig.1), covering total area of 428200 ha. Two large rivers, Wuding River and Lu River classify the whole county into two parts: north of Wuding River and west of Lu River belong to Mu Us desert, suffering heavy sandy desertification; the opposites belong to Loess Plateau, encountering serious water erosion. So in this County, wind erosion coexisting with water erosion and bad environment are notable characters. Western and southern are higher than eastern and northern with the altitude varying from 890 to 1535meters.The study area of this research is in the temperate zone continental monsoon semi-arid steppe climate with drought the most prominent climate character. Precipitation concentrates in July to September with average annual precipitation 397mm and evaporation 2085.5mm. Due to human's severe activities and careless protections, the ecological environment of study area is so fragile that 2/3 of lands are in degradation.

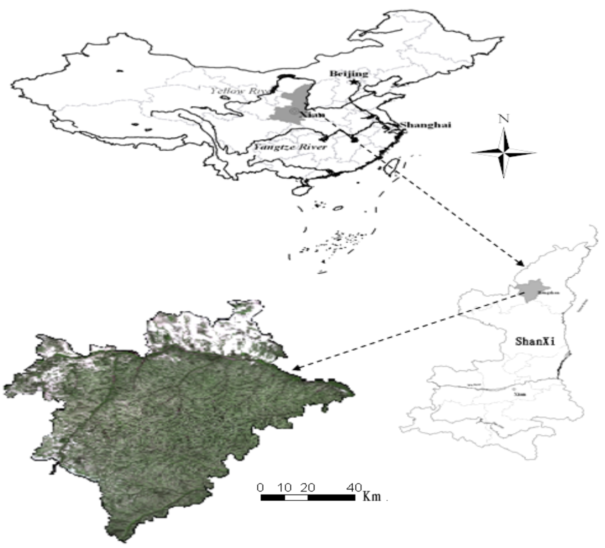

Figure.1. Study area: the hengshan County in Shanxi Province

2.2 Data acquisition

The 220-channel Hyperion data of 30m spatial resolution was acquired over the study area in northern Shanxi province on July 23, 2003 covering a ground area of approximately 8 * 12 km. The Primary technical parameters are shown in Table 1.

Band number	Spectral Range /μm	Spectral resolution /nm	Spatial resolution /m
220	0.40~2.50	10	30
Image Swath /km	Radiation accuracy / %	Quantization Rank /bit	Weight /kg
7.5	6	12	49

Table 1 The technical specifications of Hyperion

Thirty typical soil samples using GPS localization were collected. The fieldwork was undertaken during the months of September and October in 2003 between 10:00 AM and 2:30 PM on a clear, sunny day by using a high spectral resolution analytical spectral device (ASD). It operates in the visible, the near infrared and the shortwave infrared (350~2500nm). The radiometric measurements were carried out with resolution intervals of 3 nm between 350 and 1000 nm and 10 nm between 1000 and 2500 nm. Dark current and white reference (Spectral on panel) corrections were made approximately every 2~3 min. Each spectrum acquired in the field consisted of 25 individual measurements were taken consecutively and averaged by the Field Spec. The soil organic matter content was measured in the laboratory with Potassium Dichromate Capacity method and the statistical characteristics were in Table 2.

	Minimum	Maximum	Mean	Median
SOM	0.095	2.442	0.607	0.542
	Skewness	Kurtosis	Std.Dev	Cv
SOM	1.898	8.711	0.358	0.56

Table 2 The statistical characteristics of thirty soil organic matter samples

2.3 Hyperion data preprocessing

By comprehensive analyzing all the 220 bands, 82 bands were eliminated because of no signal, low signal-to-noise ratio and bad lines. Finally 138 bands were kept for the study.

The Hyperion image was radiometrically corrected by the image provider. It was then corrected atmospherically to apparent surface reflectance using Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) in ENVI [17]. After that, we performed an additional empirical line (EL) atmospheric correction due to its better performance relative to the other methods [18] by selecting Water body as faint spectrum object and thrashing floor as bright spectrum object which are measured by ASD in field observations. The EL correction forces image data to match selected known field reflectance spectra using linear regressions and in many ways corrects radiometric errors [19]. At last, the geometric correction was carried out in relation to the 1:100000 topographic map covering the study area using a polynomial approach. The correction accuracy was determined by calculating the residual errors between the value obtained by the application of the function and the true value.

3. THEORIES AND METHODLOGY

3.1 Correlation analysis

A correlation analysis was performed by computing the correlation coefficient between soil organic matter data and selected variables, the formulation is:

$$r = \frac{\sum_{n=1}^{N}(R_n - R')(SOM_n - SOM')}{\sqrt{\sum_{n=1}^{N}(R_n - R')^2 (SOM_n - SOM')^2}} \tag{1}$$

Where r is the correlation coefficient,
R is the selected variables (e.g. spectral reflectance and color indices)
n is the number of soil samples, here N is 30.
SOMn is soil organic matter content of sample n,
R’ as well as *SOM’* is the mean value.

3.2 Multivariate statistical regression

Multivariate statistical regression was selected to model the relationship between variables and soil organic matter concentrations. Multivariate statistical regression is concentrated to find the combination which is called as the linear discriminate function against the variables and the discriminate score. In this study, the function can be used to predict other pixels whose soil organic matter content isn’t measure so as to quantify the Hyperion image. The linear expression is as follows:

$$D = B_0 + B_1 X_1 + B_2 X_2 + ... + B_n X_n \tag{2}$$

Where D is a discriminate score
B_0 is an estimated constant,
Bn are the estimated coefficients
Xn are the variables.

3.3 Research procedures

After finishing the Hyperion preprocessing and lab (field) working, correlation analysis against soil organic matter was processed in succession from two aspects which were spectrum and image. The images represent the Hyperion color indices. Only the parameters of high correlation coefficients were selected to the multivariate statistical analysis and built up the regression model. Finally, this regression model was performed for soil organic matter concentration to quantify Hyperion data. To summarize the above technical stages, we provide a flow chart diagram (Fig. 2) that describes in detail the procedures.

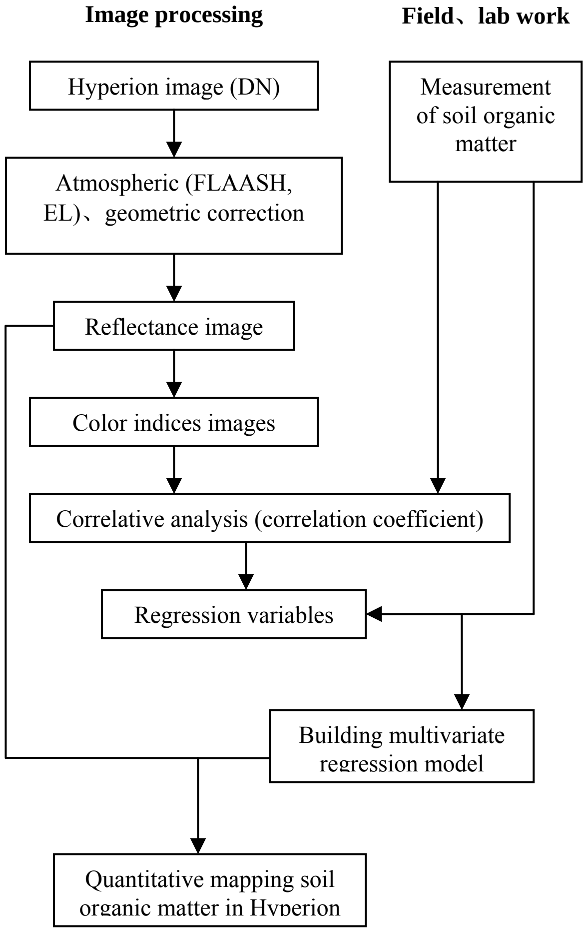

Figure.2. A flow chart that summarizes the analytical and technical stages

4. RESULTS

4.1 Image color indices

Five color indices called brightness index (BI), colouration index (CI), hue index (HI), redness index (RI) and saturation index (SI) were also selected to analyze the correlation between Hyperion image and soil organic matter content by extracting the locations of soil samples to images. These indices are calculated from the following formulations [20]:

$$\text{Brightness Index, BI} = \sqrt{\frac{(B^2 + G^2 + R^2)}{3}} \tag{3}$$

$$\text{Coluration Index, CI} = \frac{(R - G)}{(R + G)} \tag{4}$$

$$\text{Hue Index, HI} = \frac{(2 * R - G - B)}{(G - B)} \tag{5}$$

$$\text{Redness Index, RI} = \frac{R^2}{(B * G^3)} \tag{6}$$

$$\text{Saturation Index, SI} = \frac{(R-B)}{(R+B)} \qquad (7)$$

Where $R = 681\text{nm}$, $G = 569\text{nm}$, $B = 487\text{nm}$.

Where three bands in Hyperion data represent the red (R = 681nm), green (G = 569nm) and blue (B = 487nm) bands. As the indices were calculated, we could collect corresponding image values related to thirty soil organic matter samples and analyze their relations. The correlation coefficients are listed in the following (Table 3). It is found the r (correlation coefficient) values are generally lower than sensitively spectral ones, indicating images can't describe the soil organic matter features well. The probable reason which has decreased r values could have been the images were still in some influences by atmosphere and radiation although it had been corrected precedingly.

	BI	CI	HI	RI	SI
Correlation coefficient (r)	0.696	0.712	0.753	0.703	0.523

Table 4 The correlations of soil organic matter with image indices

4.2 Quantitative mapping of soil organic matter content

In most studies that use remote sensing for quantitative geologic and geomorphic mapping, a regression is set between spectral features (usually absorption depth, quantified by continuum removal) and chemical properties measured in the laboratory [21]~[23]. In this study, we showed that the transformations of reflectance could also be correlated with chemical properties. Multivariate statistical analysis was performed in SPSS software and the results were in Table 5.

Regression model	R^2	RMSE
SOM=14.375+12.456*CI* -8.276*HI*	0.78	0.45

Table 5 The results of multivariate statistical regression

In the light of table 5, According to R^2 of 0.78, we can predict the soil organic matter from the first derivative reflectance values at 78% confidence. Using this correlation, we can attain the final formulation between soil organic matter content and image colour indices as:

$$SOM = 14.375 + 12.456CI - 8.276HI \qquad (11)$$

Where *SOM* denotes the soil organic matter concentration and *CI* presents colouration index, *HI* presents hue index. With this formulation, we can hyperspectrally quantitative mapping the soil organic matter content so as to acknowledge its spatial distribution. Before quantitative mapping, we should maintain soil fragments while mask vegetation and water features in image using NDVI index of definition the values from 0.1 to 0.3. The continuous map (Fig.3) can be divided into different mapping categories according to the user's aim.

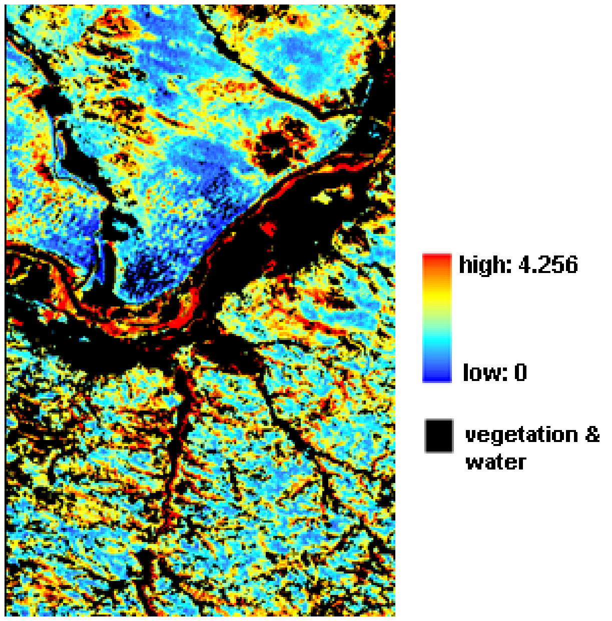

Figure.3. Continuous map of soil organic matter content

The accuracy of quantitative mapping was evaluated by calculating the R^2 value of a linear regression relating the measured soil organic matter (thirty samples) with the predicted ones. The relationship between measured and predicted values was plotted in Fig.4. The result revealed a good relationship between the measured soil organic matter content and the predicted ones with the R^2 of 0.76 that conveys we can predict the soil organic matter concentration at 76% confidence while ±24% error (e.g. soil organic matter of 0.5 would be predicted to between 0.38 to 0.62). The accuracy estimation illustrates the quantitative map of soil organic matter content is reliable and believable.

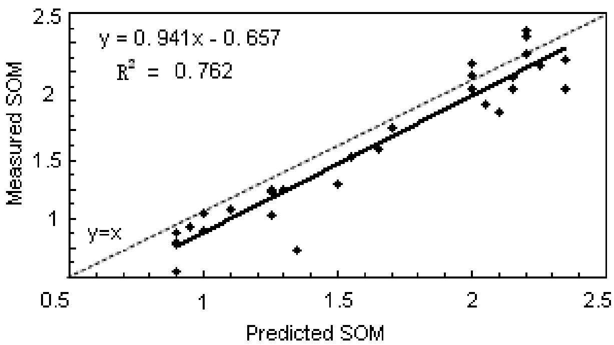

Figure.4. A scatter plot presenting the correlation against predicted SOM and measured SOM (n=30)

5. CONSLUSION

The imaging spectrometry technique, which provides near-laboratory-quality reflectance information, has the capability to obtain non-visible information and thus to produce a spatial overview of the pedogenesis processes in large scales [24]. The current study showed that it is possible to detect even a narrow and low soil organic matter and quantitatively estimate its spatial distribution in image. A facet was analyzed to be correlated with the soil organic matter: the color index (BI, CI, HI, RI, SI). The following correlation analysis which proved our hypothesis depicts that image ones (color index) has a high correlation coefficients. The multivariate regression model was performed with the first derivative reflectance of field spectrums related with soil organic matter. Knowing the regression equation, we were able to continuously map the soil organic matter using hyperspectral data with predicted accuracy of 76% which suggests a reliable result demonstrated it is a feasible and applicated way for hyperspectral image to quantitative map soil properties. In order to enhance the accuracy of quantitative mapping, we suggest correlating the field spectral data with hyperspectral data before performing regression model to images.

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