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Estimating Filed-Scale Soil Nutrient Levels in Shun Yi District, Beijing

J. L. Zhao [a,b], W. J. Huang[a]*, D. Y. Zhang[a,c], L.S. Huang[a], J.H. Luo[a]

[a]*Beijing Research Center for Information Technology in Agriculture, Beijing Academy of Agriculture and Forestry Sciences, Beijing 100097, P.R. China*

[b]*Institute of Remote Sensing Applications, Chinese Academy of Sciences, Beijing, 100101, P.R. China*

Abstract

The objective of this study is to estimate the field-scale soil nutrient levels (SNLs) of Shunyi District's croplands using 3S technologies. Based on the soil samples with GPS coordinates, a Landsat TM image was firstly utilized to identify cropland fields of the study area using support vector machine (SVM) classification module integrated with ENVI, and the overall classification accuracy reaches 87.68% and Kappa coefficient is 0.7996. Subsequently, according to the proposed classification criteria of SNLs by Beijing Soil and Fertilizer Work Station, four edaphic indicators including organic matter (OM), total nitrogen (TN), available phosphorus (AP) and available potassium (AK) were selected to estimate the filed-scale SNLs of Shunyi District. The result shows that four levels including very high, high, moderate and low are found except the very low level and they account for 0.4%, 42.3%, 53.3% and 4.0%, respectively. Furthermore, considering the spatial distribution of SNLs, it is better in the west, north and east than in the middle and south, while it is the worst in the middle.

Keywords: Field-scale cropland; Landsat TM; Shunyi District; Soil nutrient levels; Spatial interpolation

1. Introduction

As a valuable nonrenewable natural resource, cropland serves as several important economic and environmental functions, which is the most basic survival condition for human being, crops, livestock, etc.

* Corresponding author. Tel.: +86-10-51503647; fax: +86-10-51503750.
E-mail address: yellowstar0618@163.com.

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[1]. Nevertheless, increases in rapid population growth and economic activities have inevitably led to a drastic reduction of cropland especially in those more economically developed municipalities such as Beijing, Shanghai, Shenzhen, etc. To meet the requirements of economic development & residential growth, lots of fertile croplands have been converted to other types of agricultural uses and various constructions [2]. On the other hand, a great number of sources of heavy metals, which come from domestic waste, chemical industry, transportation, etc., have placed a considerable influence on human health [3]. At present, the reduction in cropland quantity and quality are the two major limiting factors affecting food safety. Therefore, on the basis of strictly stopping cropland quantity from being continuously reduced, improving cropland quality is the more effective measurement for sustainable management of land resources [4, 5]. Hu et al. (2007) explored the spatio-temporal variability of soil organic matter (SOM) in the urban–rural transition zone of Beijing [6]. Chen et al. (2005) collected samples from 30 urban parks of Beijing to assess the concentration of potentially harmful heavy metals in the soil [7]. Chen et al. (2004) conducted a survey on current fertilizer practices and analyzed their effects on soil fertility and soil salinity from 1996 to 2000 in vegetable production in the Beijing region [8]. Zhang et al. (2006) investigated the soil organic carbon (SOC) changes by collecting 197 soil samples from 42 soil sites in Yanhuai Basin, Beijing, China [9].

To summarize the above studies, it is easy to find out that they mainly rely on the field sample data concerning the cropland quality monitoring or soil nutrient evaluation. When collecting soil samples, it is inevitable that some errors were introduced due to the existence of subjective human experience. Furthermore, traditional survey method is more labor-intensive and time-consuming. Conversely, Remote Sensing (RS), Geographic Information System (GIS) and Global Positioning System (GPS) have provided a better solution for such a problem at more extensive spatial and temporal scales. Taking Shunyi District, Beijing as the study area, this study is aimed at estimating the soil nutrient levels (SNLs) using advanced "3S" technologies. Specifically, GPS is used to record the coordinates of soil samples, RS is used to identify filed-scale croplands of the study area and GIS is utilized to perform spatial analysis and statistics using those edaphic indicators of samples.

2. Materials and methods

2.1. Description of the study area

Shunyi District is located between latitudes 40°00'-40°18' N and longitudes 116°28'-116°58' E, which lies to the northeast of central Beijing. Arable cropping, residential and industrial use and forest are the three major types of land use. This region has a warm temperate zone wet continental monsoon climate with an average annual temperature of 11.5 °C. The frost-free period lasts around 195 days, and annual sunshine duration is 2,750 hours and average annual relative humidity is about 50%. It has a fertile soil ranging from sandy to loamy soils and the topography is mostly plains with a small remote hilly area of the northeastern corner, so Shunyi District is a farming community [10]. However, in the past decades, land use in this area has undergone a quick change due to the fast economic growth and urbanization, characterized by conversion of arable land into built-up and green areas.

2.2. Data and preprocessing

The used data consist of Landsat TM satellite image (2006) with 30 m resolution, soil sample points, and agricultural statistic data. Originally, the image was just systematically processed by radiometric and geometric corrections, so further corrections must be firstly carried out. In this study, the FLAASH (Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes) atmospheric correction module integrated with ENVI (Environment for Visualizing Images) environment was used to perform the radiometric calibration and atmospheric correction. While the geometric correction was performed in the orthocorrection model of Leica Photogrammetry Suite (LPS), which is integrated with the ERDAS (Earth Resources Data Analysis System) imagine processing software. Additionally, field survey was also carried out to derive the ground census data of soil fertility. Table 1 shows some parameters of several soil samples surveyed in Shunyi District. Those 435 samples with GPS coordinates were firstly exported to shapefile format in Arcmap. Furthermore, they were spatially analyzed and interpolated using the spatial analyst tools to exclude abnormal values and find out the spatial distribution.

Table 1. Some parameters of several soil sample points in Shunyi District

No.	Planting features	Organic matter (g/kg)	Available P (mg/kg)	Available K (mg/kg)	Total nitrogen (g/kg)	Soil pH
1	Summer maize	17.3800	20.1700	96.0000	0.9200	8.4900
2	Winter wheat	17.2800	10.3400	90.0000	0.9700	8.2800
3	Spring maize	13.3600	30.7900	82.0000	0.8500	8.1200
4	Summer maize	18.5500	15.4500	108.0000	1.1500	8.1300
5	Spring maize	19.2800	85.2500	160.0000	1.2100	7.9300

2.3. *Estimation method*

The classification criteria used here is the regulations for gradation and classification on soil nutrient developed by Beijing Soil and Fertilizer Work Station (BSFWS) in December 2006. In this regulation, four edaphic indicators were added to the estimation procedure including organic matter (OM), total nitrogen (TN) or alkali-hydrolyzed nitrogen (AN), available phosphorus (AP) and available potassium (AK). Additionally, this estimation method also gives the weight coefficients and scores of each edaphic indicator (Table 2) based on analyzing the characteristics of soil nutrients and contribution proportion of each indicator of Beijing. Eq. 2 is the proposed comprehensive evaluation index by the work station.

$$SNI = \sum F_i \times W_i \qquad (i = 1, 2, 3, \ldots\ldots, n) \tag{1}$$

Where SNI is the soil nutrient index; F_i is the value of the *i*th edaphic indicator; W_i is the weight coefficient of the *i*th edaphic indicator; *n* is the total selected edaphic indicators.

Table 2. Evaluation scores and corresponding weight coefficients of soil nutrient indicators of Beijing*

Level	OM (g kg-1)/ Score	TN (g kg-1)/ Score	AN (g kg-1)/ Score	AP (g kg-1)/ Score	AK (g kg-1)/ Score	SNI
Very high	≥25/100	≥1.20/100	≥120/100	≥90/100	≥155/100	100-95
High	(25-20)/80	(1.20-1.00)/80	(100-90)/80	(90-60)/80	(155-125)/80	95-75
Moderate	(20-15)/60	(1.00-0.80)/60	(90-60)/60	(60-30)/60	(125-100)/60	75-50
Low	(15-10)/40	(0.80-0.65)/40	(60-45)/40	(30-15)/40	(100-70)/40	50-30
Very low	<10/20	<0.65/20	<45/20	<15/20	<70/20	30-0
Weight	0.3	0.25		0.25	0.20	-

*Data source: Beijing Soil Resource Management Information Network, http://202.112.163.254:8008/new%20-soil/index.html.

There are two processes to derive filed-scale SNLs. The first step is to identify the croplands of Shunyi District, Beijing and the other is to estimate the SNLs. To understand the spatial distribution of croplands, a Landsat TM image of 2010 was acquired and the support vector machine (SVM) supervised classification method was utilized to obtain the remote sensing-based croplands. In this study, after the data was processed, the commercially available software ENVI (Environment for Visualizing Images) was used to perform the SVM classification. The SVM module was integrated in the ENVI and several parameters were required to complete the classification. To derive the optimized classification parameters for ENVI-SVM classification module, the trial-and-error method was used [11, 12]. Firstly, a small sample area was used to derive the optimum parameters including penalty parameter, gamma in kernel function. Subsequently, classification experiments were continually carried out by changing the corresponding parameters in the SVM module. Finally, those parameters with the highest accuracy and consistency were selected to classify the entire image and croplands were derived after post-classification. After finishing the first step, selected edaphic indicators of filed survey samples were processed to create trend surfaces using Kriging interpolation method [13]. Furthermore, those interpolated surfaces were calculated to derive the soil nutrient index in the raster calculator of spatial analyst module of ArcMap.

3. **Results**

3.1. Identification of cropland fields

Fig. 1 shows the original Landsat TM image (a) and cropland identification result (b). Fig. 1(a) is a false composite image using Band 4, Band 3 and Band 2 of Landsat TM. It is clear that the croplands distribute almost everywhere in the study area except the southwestern part and northeastern corner because of built-up areas and forest. As can be seen in Fig. 1(b), croplands keep the spatial distribution with large plots in the east and west than in the north and south. In addition, in the intersection between Shunyi District and Miyun County, croplands with small patches irregularly distribute due to undulating topography. It can be interpreted that human activates have exerted a disturbance on the natural distribution of croplands.

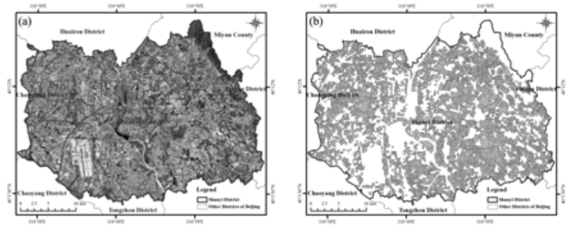

Fig. 1. (a) Original Landsat TM false composite image; (b) identified cropland map (b) of Shunyi District

3.2. Estimation of soil nutrient levels

After calculating soil nutrient index, further level classification was performed using the criteria (Table 2). It is obvious that the very low level of soil nutrient is absent in this region (Fig. 2). After statistically analyzing the other four levels (very high, high, moderate and low), it is found that they account for 0.4%, 42.3%, 53.3% and 4.0%, respectively. The result shows that the high and moderate level soil nutrients dominate most of this district's soil, and the percentage of very high level is very small. Considering the spatial distribution of SNLs, it can be obviously found that the very high level soil only exits in the eastern part of this district. Most of high level soil distributes in the northern and eastern parts. Moderate level soil distributes almost every direction across the whole district. Conversely, low level soil just mainly distributes in the middle parts. Taken as a whole, the soil nutrient is better in the west, north and east than in the middle and south, while it is the worst in the middle.

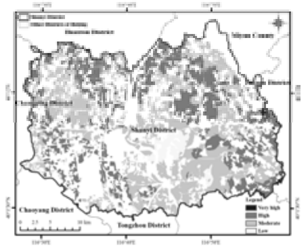

Fig. 2. Spatial distribution of identified field-scale soil nutrient levels of Shunyi District

3.3. Classification accuracy assessment

To validate the classification of cropland fields, two methods were adopted. One is to construct a confusion matrix for deriving the overall classification accuracy and Kappa coefficient (Eq. 2) and the other is to compare the cropland acreage between Landsat TM-derived and the agricultural statistic data.

$$Kappa = \frac{N\sum_{i=1}^{k} x_{ii} - \sum_{i=1}^{k} x_{i\Sigma} x_{\Sigma i}}{N^2 - \sum_{i=1}^{k} x_{i\Sigma} x_{\Sigma i}} \qquad (i = 1, 2, \ldots, k) \tag{2}$$

where N is the total number of pixels in all the ground truth classes; x_{ii} is the confusion matrix diagonals; k is the total classes; $x_{i\sum}$ is the sum of the ground truth pixels in i class; $x_{\sum i}$ is the sum of the classified pixels in that class.

To identify the cropland fields from Landsat TM image, cropland, water body, and non-cropland were used as the regions of interest (ROIs). As a result, 435 cropland pixels, 123 water body pixels and 367 non-cropland pixels were selected in the image. Depending on the ground truth from SPOT image with higher spatial resolution than Landsat TM, a confusion matrix was constructed (Eq. 2). The overall classification accuracy is 87.68% and Kappa coefficient is 0.7996, which indicates that it can be used to estimate the SNLs of the study area [14]. Additionally, the Landsat TM-derived cropland acreage is 520 km^2 and the statistic data is 513 km^2, so the overall accuracy is 1.01% (520/513*100). The reason for such a phenomenon is that it just classifies those pixels as cropland with same pixel homogeneity of specified cropland ROIs for remote sensing-based cropland identification. Conversely, it primarily considers land-use properties for the statistic data. Furthermore, to validate the classification accuracy of SNLs, the statistic data from BSFWS was used to compare the spatial interpolation-derived data. The comparison results show that about 53.3% of croplands are in moderate level compared with 53% of statistic data, and there is no very low level soil nutrient for both data.

Conclusions

In this study, depending on the proposed classification criteria by Beijing Soil and Fertilizer Work Station, four edaphic indicators including OM, TN, AP and AK were selected to estimate the filed-scale SNLs of Shunyi District, Beijing. We drew several conclusions: (1) As shown in Fig. 1, croplands distribute almost everywhere in the study area except the southwestern part and northeastern corner owning to built-up areas and forest. (2) In the study area, four levels of soil nutrient including very high, high, moderate and low can be found except the very low level soil, which account for 0.4%, 42.3%, 53.3% and 4.0%, respectively. (3) Considering the spatial distribution of SNLs, the soil nutrient is better in the west, north and east than in the middle and south, while it is the worst in the middle due to the human activities. Therefore, this study can provide an alternative method to estimate the SNLs at a larger spatial scale under the help of advanced 3S technologies other than traditional statistical method.

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