High-Spectral Inversion Based on Characteristic Band ihe Three-River Headwater Region of Soil Total-Nitrogen

[1, 2] Hui Lin, [2] Ruiliang Pu, [1]Lijuan Wang, [2,3] Changchun Li, [1]Congying Shao

[1] *School of Geodesy and Geomatics*, Jiangsu Normal University, Xuzhou, Jiangsu, 221116, P.R. China
[2] *Department of Geography*, University of South Florida, Tampa, FL, 33620, USA
[3]*Department of Precision Manufacture Engineering*, Suzhou Institute of Industrial Technology, Suzhou, Jiangsu, 215104, P.R. China

***Abstract* — In this paper, in 2012 and 2013 two of the Three-River Headwaters Region of soil total-nitrogen, data combined ASD FieldSpec 4 made by America spectroradiometer measured spectral reflectance of soil sample chamber data model MSLR and ANN methods modeling. The spectral data is mainly composed of original spectral reflectance(REF) through nine point weighted moving average obtaining four forms of data: first derivative reflectance(FDR), second derivative reflectance(SDR), Log(1/R), band depth(BD), gaining the model input variable of characteristic band. The sample was divided into total samples and 5 types of soil by analyzing spectral reflectance of typical soil of the Tibet Plateau in the three-river headwaters region, which is served as a reference for recognizing the type of soil. Comparing the model of MSLR and ANN, we can conclude that the precision of modeling with all band (350~2500nm) and verification is wider than characteristic bands (500~900nm, 1400~1500nm, 1900~2000nm and 2200~2300nm), which has better stability and efficiency and the precision of nonlinear model of ANN is obviously better than MSLR. Modeling with total sample has better stability and precision of inversion for that modeling with overall sample is able to estimate roughly total nitrogen composition of soil, which shows a stable model and situation of verification.**

Keywords - High-spectral inversion; types of soil composition; transformation; MSLR model; ANN model

I. INTRODUCTION

Soil total-nitrogen is an important indicator of soil fertility, and research of soil total-nitrogen has certain practical value. The conventional soil nutrient of chemical method has been unable to meet the research needs [1,2]. With the advantage of its high-spectral resolution and flexible classification recognition method, hyper-spectral makes recognition of soil chemical element using quantitative or semi-quantitative classification possible. Therefore, the study on soil hyper-spectral estimation of soil organic matter content is of great significance.

In recent years, people committed to the improvement of model wish to improve the accuracy of the model by conversing the reflectivity appropriately. In terms of spectral reflectance of organic matter, domestic and foreign scholars have different views on the selection of sensitive bands and the establishment of inversion model. At present, applying soil spectrum to estimation of the relevant of properties of soil mainly takes advantage of statistical methods, for example multiple stepwise regressions, partial least squares regression. The relationship between soil organic matter and hyper-spectra is complex, so the simple regression model in dealing with complex problems such as the nonlinear and the multi-collinearity still has shortcomings and is difficult to satisfy the research needs [3, 4]. Therefore, this paper analyzes and summarizes the relationship between soil total-nitrogen, five soil spectral transformation and the spectral reflectance , as well as establishes a full band model of soil total-nitrogen content based on two kinds of model method(MSRL and ANN), and introduces the method of establishing model by selecting high correlation characteristic bands, analyzing the feasibility, compares two methods of data input and gaining the pattern of modeling characteristics, which can provide certain theoretical basis for the future research of soil composition.

II. MATERIALS AND METHODS

A. *Collection of Samples*

Samples were collected two batches, the first batch of 2012 August7-17 and the second batch of 2013 August 17-27. The main soil sampling point (Fig.1) distributes in the three-river headwaters region of Yushu County, Maduo County (a small number of samples in Zaduo County, Nangqan County).

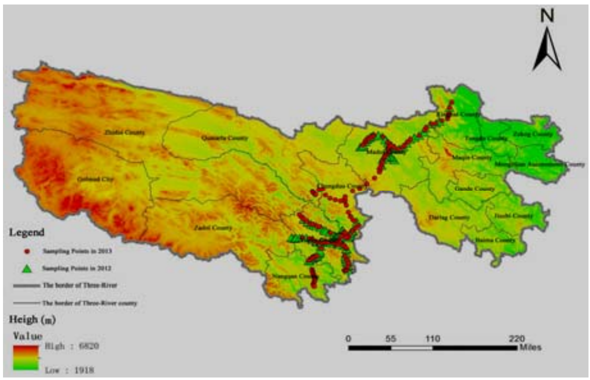

Fig.1 Sampling Distribution Map

The number of soil samples collection is 296.Soil samples were surface soil ranging 0~30cm, with each sample collects soil weighting 1kg, each sample point position with a handhold GPS and sealed into the compact bags after uniform mixing by filling field soil sampling record table[5,6]. Under the condition of indoor natural, air-dry soil samples were lately grinded, eliminating animal debris, rocks and external intrusion[7], followed by 20 mesh, 60mesh, 100mesh sieving. The solved sample were divided into three parts ,one for the analysis of chemical composition of soil, second for spectral measurement and third for future reference by compacting bag.

B. *Analysis and Testing*

Spectral reflectance of soil samples were collected by using an ASD FiedlSpec 4 spectrometer, which covers the visible and near infrared spectral range. Interior geometric condition: halogen lamp of 1000W light source is capable of providing parallel light, the distance from source to the soil sample is 30cm, the probe distance of soil sample surface is 15cm, zenith angle is 30°, the dish holding soil samples is directly below the probe, and the diameter of sample plate is 15cm with 2.5cm depth. When we hold soil sample, the application of glass should be compacted gently, with light covering the whole field of view [8-10]. Experiment was carried out in the dark, using white board calibration before the measurement of soil spectral reflectance. Each soil sample was tested four times and collected one time at each rotation of 90°, gathering five at a time with a total of 20 spectral reflectance curve of a soil sample, which uses the arithmetic average as the final spectral results after excluding abnormal curve, we export the spectrum of *.asd original spectrum file using the instrument cabin ViewSpec, for subsequent processing. Using Elementar Variol EL element analyzer produced by the German company completes soil total-nitrogen content test, which analyzes samples of conventional organic element content. The experiment mainly uses high-temperature combustion method [11]. Table1 showed statistical characteristics of soil total-nitrogen content.

TABLE I. STATISTICAL CHARACTERISTICS OF SOIL TOTAL-NITROGEN CONTENT

	Agrotype	Maximum （g·kg-1）	Minimum （g·kg-1）	Average （g・kg-1）	Standard deviation	Coefficient of variation %
Soil total-nitrogen content （g·kg-1）	Total sample	16.00	0.55	4.40	2.76	62.89
	Alpine meadow soil	16.00	0.55	5.40	2.68	49.69
	Alpine steppe soil	12.90	0.70	2.57	2.28	88.60
	Mountain meadow soil	7.63	0.80	3.16	1.85	58.62
	Bog soil	12.9	1.00	3.75	2.93	78.17
	Gray-drab soil	9.85	1.30	5.48	2.18	39.72

Table I shows that in all types of soil bog soil variability is strongest and gray-drab soil variability is weakest. Research shows that the larger the coefficient of variation of soil composition is, estimating by a spectral reflectance, the stronger the sample representativeness is, so in this paper, the data is representative.

C. *Spectrum Data Processing*

Some errors are inevitable in the process of spectral determination, so we need to preprocess the spectrum. Through statistical analysis of soil composition and comparison of the spectral reflectance of soil samples, we removed 15 invalid samples, and final chose 281 soil samples of five soil types for subsequent spectral pretreatment and estimation modeling of soil total-nitrogen content in the study area. In this paper, the pretreatment work firstly is smoothing the spectral curve in the support of ENVI4.8. The Spectral module uses 9 point weighted moving average method to process original spectral reflectance to obtain the original spectral reflectance (REF). Lately, by the differential transform on the REF data, the estimation of the inversion of soil composition can achieve better results, but the high order differential conversion is easy to eliminate some effective information of the soil, which may affect the precision of inversion [12]. This paper main chose four kinds of forms of mathematical transformation process, which were first derivate reflectance, second derivate reflectance, Log (1/R) and band depth.

D. *Data Modeling*

For soil composition inversion of different agrotype, we used MSLR and ANN to establish the model, and there are a variety of programs to set up BP neural network, for each indicator of agrotype [13]. The paper designs four scenarios specific design in Table II. Modeling accuracy and the ability to verify the prediction accuracy in this paper can be evaluated by the following parameters: modeling determination coefficient (R^2), Root Mean Square Error (RMSE), verification determination coefficient(r), ratio of performance to deviation (RPD) [14].

TABLE II. BP NEURAL NETWORK MODEL TRAINING PROGRAM

Network parameters	Scheme 1	Scheme 2	Scheme 3	Scheme 4
Network structure	Single hidden layer BP	Single hidden layer BP	Single hidden layer BP	Single hidden layer BP
Neuron in hidden layer	25	30	35	40
Hidden layer transfer function	Tansing	Logsing	Tansing	Logsing
Training function	Traincgf	Traincgb	Traincgb	Traincgf

E. Selection of Characteristic Spectrum

Influenced by agrotype, soil spectral curve shows their own characteristic and differences [15]. The spectral curves of several kinds of typical soil types were analyzed in Tibet Plateau, and this study summarized the spectral characteristics of different soil types, which provided a basis for the study of identification of soil type by soil spectral reflectance.

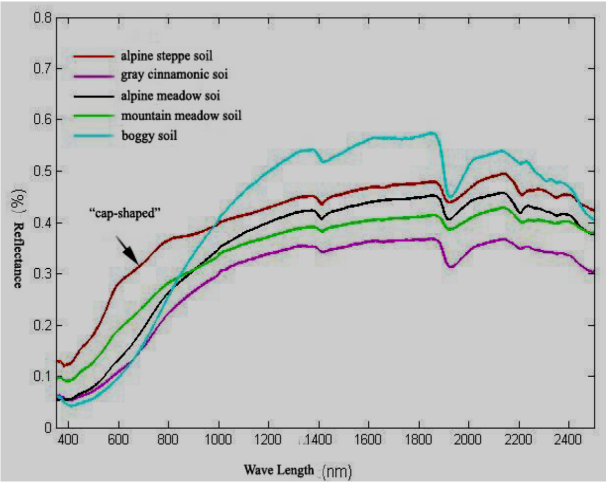

Fig.2 The Original Spectral Reflectance Curve of Various Soil Types

Fig 2 shows the original spectral reflectance curve of five soil types (the original spectral reflectance curve have been smoothed), and that the trend of different soil types was consistent in full band. By analyzing, we can conclude that 350~1300nm uplifted continuously and 1400nm was interrupted by a shallow valley of moisture absorption, and then band range from 1400nm to1850nm continued to rise, but the extent of uplift was more gentle than the previous one, and 1900nnm was again interrupted by a deep valley of moisture absorption, and 1900~2200nm was the third time the small-scale uplift, and 2200nnm was interrupted by the absorption of clay minerals shallow valley, and finally 2200~2500nm declined gently for the first time, and the curve showed downward trend because of the impact of noise.

To some extent, soil composition of various soil types determined the reflectance values of soil spectral curve and the shape of the curve [16], and 350~1000nm was the most obvious difference of different soil types. In this region, soil spectral reflectance curve was divided into two types, one was ordinary type (alpine meadow soil, mountain meadow soil, bog soil, gray-drab soil), which rose faster, when the uplift curve was smooth; Another was kind of "cap" special curve (comments of Fig 2), namely alpine steppe soil, and this special "cap" had a certain relationship with the content of soil composition. Low soil total-nitrogen content of alpine steppe soil causes the within the scope of spectral "cap" uplift, which could be used to distinguish between alpine steppe soil and other soil types, to observe soil spectral reflectance data to identify the effect of soil types.

Analyzing of the correlation of spectral reflectance and soil composition content of five kinds of transformation, it revealed hyper spectral data and the soil components had higher correlation in the wavelength range(350 ~ 1000nm) , and the trend was consistent. So in order to simplify the model, shorten the operation time of the model and improve the precision of the model , we decided to select four bands (500 ~ 900nm, 1400 ~ 1500nm, 1900 ~ 2000nm and 2000 ~ 2200nm)of the correlation coefficient reaching 0.4, which was used to model and validate characteristic band .

III. RESULTS AND ANALYSIS

A. Full Band Hyper Spectral Inversion of Different Soil Types

Full band component inversion of different soil types is established by using two methods MSLR and ANN, with five kinds of spectral reflectance data from 350nm to 2500nm and soil total-nitrogen content as input variables, establishing a model to estimate the five types of soil in the study area soil composition. All modeling and validation was realized in Matlab 2010 b.

1) Total Nitrogen Content of full Band Inversion

(1) Multiple Stepwise Linear Regression Model

The results of modeling and verification of MSLR inversion soil nitrogen content, using full band spectral data, were shown in Table III.

TABLE III. THE INVERSION RESULTS OF TOTAL NITROGEN CONTENT OF MSLR

Agrotype transformation form		Modeling accuracy		Verification accuracy		
		R^2	RMSE	r	RMSE	RPD
Alpine meadow soil	**REF**	**0.72**	**1.43**	**0.80**	**1.54**	**1.40**
	FDR	0.83	0.97	0.78	1.67	1.29
	SDR	0.99	0.05	0.71	2.69	0.80
	Log（1/R）	0.93	0.62	0.70	1.75	1.23
	BD	0.91	0.69	0.65	1.90	1.13
Alpine steppe soil	REF	0.94	0.63	0.83	0.96	1.47
	FDR	0.94	0.79	0.80	1.20	1.18
	SDR	0.99	0.02	0.83	0.89	1.58
	Log（1/R）	**0.92**	**0.73**	**0.92**	**0.84**	**1.68**
	BD	0.98	0.35	0.49	10.54	0.13
Mountain meadow soil	**REF**	**0.79**	**0.85**	**0.90**	**0.78**	**2.33**
	FDR	0.91	0.57	0.81	1.09	1.67
	SDR	0.99	0.01	0.77	1.26	1.44
	Log（1/R）	0.82	0.80	0.91	0.80	2.28
	BD	0.84	0.75	0.89	1.59	1.14
Bog soil	REF	0.98	0.44	0.72	1.38	1.33
	FDR	0.99	0.05	0.46	2.11	0.87
	SDR	0.93	0.93	0.23	2.37	0.78
	Log（1/R）	0.97	0.59	0.71	1.46	1.26
	BD	**0.98**	**0.41**	**0.82**	**1.00**	**1.84**
Gray-drab soil	REF	0.93	0.61	0.20	2.97	0.67
	FDR	**0.99**	**0.01**	**0.86**	**1.04**	**1.92**
	SDR	0.99	0.04	0.03	3.93	0.51
	Log（1/R）	0.92	0.67	0.22	2.95	0.68
	BD	0.99	0.04	0.74	1.52	1.32
Total sample	REF	0.88	0.94	0.84	1.29	1.71
	FDR	0.84	1.07	0.82	1.37	1.61
	SDR	0.99	0.01	0.73	2.20	1.00
	Log（1/R）	**0.89**	**0.90**	**0.88**	**1.17**	**1.88**
	BD	0.88	0.91	0.85	1.28	1.72

Best transform form inversion results of each soil type in the table was marked in bold. It can be seen from the table, the difference of the precision of MSLR model inversion between various soil types and the total sample total nitrogen is bigger, and precision of each soil type model was different. The best precision index of alpine meadow soil was REF, which had the ability to estimate soil total nitrogen, and the standard of the best form of modeling was RDP, which verified the accuracy of model. The best indicator of alpine steppe soil was the Log (1 / R) because the modeling accuracy and validation accuracy achieved better accuracy, which shows that the indicator can roughly calculate that the total nitrogen content of soil types. The best indicator of mountain meadow soil was REF. Although modeling accuracy was not high, the model achieved excellent test precision, which showed the model is not very stable and that the stability remained to be improved. BD index of bog soil roughly estimated soil total-nitrogen content, and the modeling precision was higher. FDR indicator of gray-drab soil had high modeling accuracy, but verification accuracy is not high, due to fewer soil samples and the increase of random of sample points, so the result had great uncertainty. All models can roughly be estimated, in addition to the SDR indicators of total sample, which did not meet RDP more than 1.4 and the accuracy of the total sample modeling had better stability and higher precision than classing soil type. Because of enough sample points of total sample, it tended to weaken the characteristic difference of various soil types, which was conducive to establish a more stable model, and it also reduced the prediction difference between 5 kinds of transformation form[17].

Because of more modeling methods and more data types in soil total-nitrogen of MLSR inversion, we selected the best indicator of the each soil type and total sample to map, showing in the figure3.

TABLE IV. THE VERIFICATION ACCURACY OF TOTAL NITROGEN MODELING

Agrotype transformation form optimal scheme			Modeling accuracy		Verification accuracy		
			R^2	RMSE	r	RMSE	RPD
Alpine meadow soil	REF	Scheme 2	0.95	0.51	0.84	1.22	1.76
	FDR	**Scheme 3**	**0.85**	**0.99**	**0.84**	**1.17**	**1.84**
	SDR	Scheme 1	0.91	0.72	0.79	1.55	1.39
	Log（1/R）	Scheme 3	0.90	0.75	0.82	1.26	1.71
	BD	Scheme 3	0.86	0.89	0.82	1.32	1.63
Alpine steppe soil	REF	Scheme 4	0.95	0.62	0.91	0.73	1.93
	FDR	**Scheme 1**	**0.98**	**0.40**	**0.91**	**0.72**	**1.96**
	SDR	Scheme 1	0.93	0.74	0.84	1.18	1.19
	Log（1/R）	Scheme 1	0.94	0.63	0.86	0.98	1.44
	BD	Scheme 3	0.95	0.65	0.90	1.11	1.27
Mountain meadow soil	REF	Scheme 1	0.90	0.61	0.84	0.98	1.86
	FDR	Scheme 2	0.88	0.66	0.92	0.78	2.33
	SDR	Scheme 1	0.88	0.66	0.90	1.01	1.80
	Log（1/R）	Scheme 3	0.85	0.78	0.82	1.05	1.73
	BD	**Scheme 3**	**0.94**	**0.46**	**0.95**	**0.72**	**2.53**
Bog soil	**REF**	**Scheme 2**	**0.97**	**0.61**	**0.96**	**0.53**	**3.47**
	FDR	Scheme 3	0.95	0.79	0.94	0.67	2.75
	SDR	Scheme 3	0.97	0.67	0.89	0.91	2.02
	Log（1/R）	Scheme 2	0.96	0.70	0.82	1.11	1.66
	BD	Scheme 4	0.95	0.73	0.95	0.87	2.11
Gray-drab soil	REF	Scheme 1	0.80	1.12	0.55	1.52	1.32
	FDR	Scheme 4	0.94	0.64	0.68	1.65	1.21
	SDR	**Scheme 1**	**0.80**	**1.07**	**0.79**	**1.09**	**1.83**
	Log（1/R）	Scheme 2	0.83	0.97	0.66	1.29	1.55
	BD	Scheme 2	0.74	1.23	0.84	1.11	1.80
Total sample	REF	Scheme 2	0.93	0.73	0.85	1.32	1.67
	FDR	**Scheme 3**	**0.94**	**0.64**	**0.88**	**1.19**	**1.85**
	SDR	Scheme 1	0.94	0.65	0.85	1.31	1.68
	Log（1/R）	Scheme 3	0.93	0.71	0.86	1.28	1.72
	BD	Scheme 4	0.92	0.75	0.87	1.19	1.85

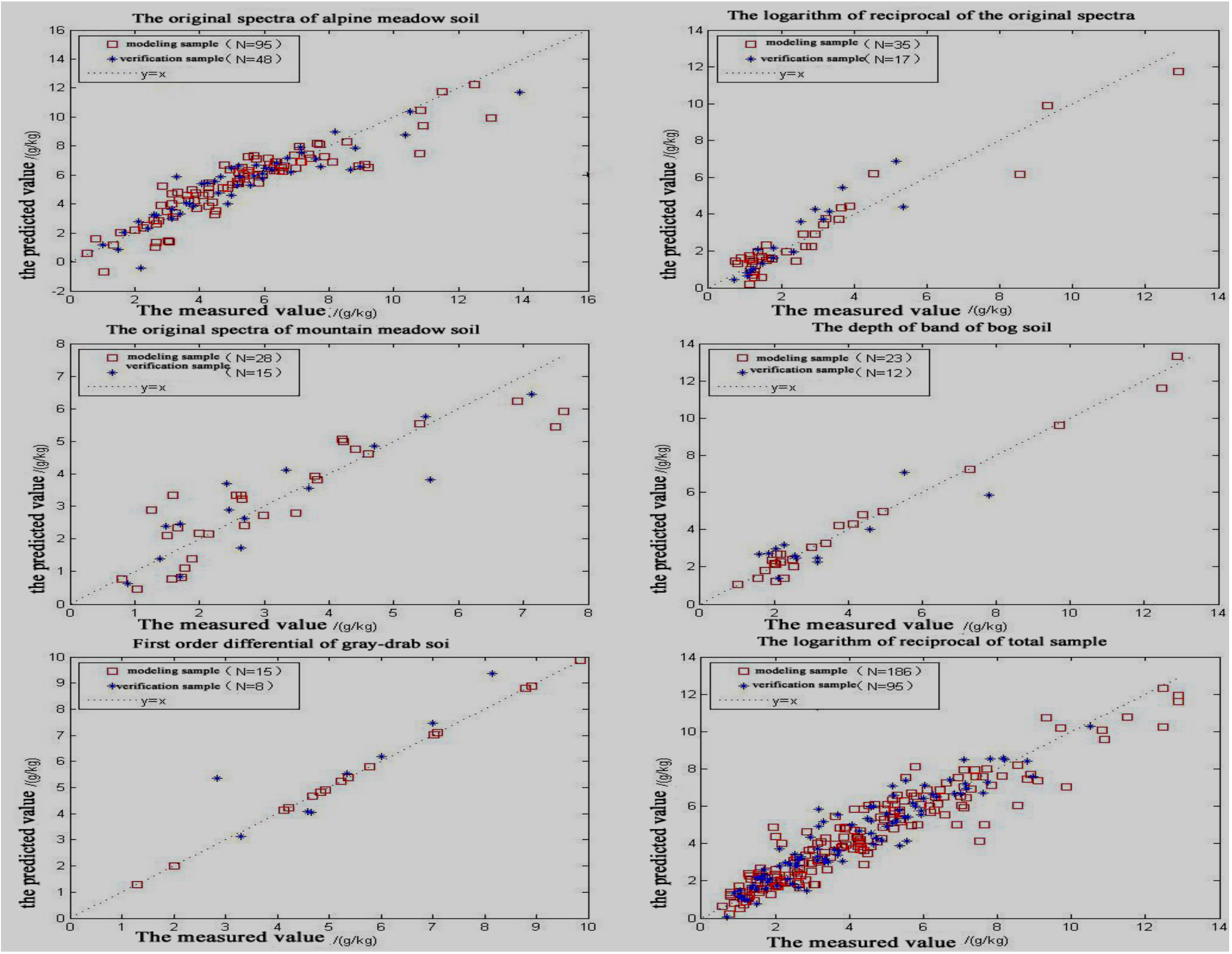

Fig.3 The Results of Full Band Model and Verification Accuracy of Total-Nitrogen of MSLR

(2) Artificial Neural Network Model

The results of modeling and verification of total nitrogen data of BP neural network were shown in Table 4. Because of significant difference of each solution

From the above table, the result of the source area of the soil total nitrogen content estimating by the BP neural network model was good and much better than MSLR, probably because the relationship between the spectral data and total nitrogen content is not a simple linear, while the ANN had strong nonlinear processing capability. REF and other forms of four kinds of transformation of soil total-nitrogen can achieve good prediction accuracy due to ANN, and REF of bog soil was the highest prediction of RPD

precision and limited space, we only listed the best solution, which would be no longer illustrated below.

(R^2 =0.97,RMSE=0.61,r=0.96,RMSE=0.53,RPD =3.47); reaching the excellent estimation accuracy. The SDR transformation of alpine steppe soil was the lowest level of prediction (RPD=1.19). In differential transformation, the first derivate reflectance can preferably predict the soil total nitrogen content of research area, and the effect of second derivate reflectance was unfavorable. Because of enough sample points of total sample and encompassing all soil types, it tended to weaken the characteristic difference of various soil types, which reduced the prediction difference between 5 kinds of transformation form, and PDS was above 1.67, with the characteristics of rough estimation of sample soil total nitrogen content. Classifying soil types was more likely to distinguish their suitable spectral transformation, and it may be that the spectral characteristics of each kind of transformation during the mathematical transformation of original spectrum reflectance data that strengthened or weakened were different, and the characteristics of the difference of each soil type highlighted the difference of various transformations of the various soil types [18].

From Table 3 and Table 4, the precision of nonlinear ANN was better than MSLR. Modeling precision of ANN was high and the transformation of validation (RPD>1.4) was more than MSLR. But MSLR model was easier to achieve excellent model accuracy, suggesting that there are obvious differences between principle and inversion ability of two models, and the pursuit of ANN was the stability of the model, while MSLR paid more attention to excavate great transformation of soil type.

IV. CHARACTERISTIC BAND HYPER SPECTRAL INVERSION OF DIFFERENT SOIL TYPES

In order to simplify the model, shorten the operation time of the model and improve the precision of the model, this chapter uses MSLR and ANN for the absolute value of correlation coefficient over 0.4 four band (500 ~ 900nm, 1400 ~ 1500nm, 1900 ~ 2000nm and 2000 ~ 2200nm)to model and predict, explore the characteristics of high-spectral band reflectance data to simplify the method of inverting soil total-nitrogen content, evaluating precision, and contrasted and analyzed the applicability of the method on the estimation of soil composition in the three-river headwaters region[19].

A. Total Nitrogen Content of Characteristic Band Inversion

1） Multiple Stepwise Linear Regression Model

The results of modeling accuracy verification accuracy of MSLR of soil nitrogen content, using characteristic band spectral data, were shown in Table V.

TABLE V. THE MODELING RESULTS OF CHARACTERISTIC BAND OF SOIL NITROGEN

Agrotype transformation form		Modeling accuracy		Verification accuracy		
		R^2	RMSE	r	RMSE	RPD
Alpine meadow soil	REF	0.81	1.03	0.61	2.12	1.01
	FDR	0.80	1.05	0.71	1.78	1.21
	SDR	0.75	1.20	0.69	1.90	1.13
	Log（1/R）	**0.92**	**0.66**	**0.74**	**1.53**	**1.41**
	BD	0.85	0.90	0.62	2.23	0.96
Alpine steppe soil	**REF**	**0.97**	**0.47**	**0.85**	**0.78**	**1.81**
	FDR	0.92	0.77	0.89	0.81	1.74
	SDR	0.92	0.80	0.60	2.14	0.66
	Log（1/R）	0.94	0.71	0.47	2.23	0.63
	BD	0.97	0.45	0.70	3.46	0.41
Mountain meadow soil	REF	0.86	0.80	0.54	1.96	0.93
	FDR	0.94	0.50	0.82	1.13	1.61
	SDR	0.90	0.62	0.63	1.77	1.03
	Log（1/R）	**0.86**	**0.69**	**0.95**	**0.59**	**3.08**
	BD	0.90	0.68	0.77	3.54	0.51
Bog soil	REF	0.95	0.72	0.61	1.41	1.30
	FDR	0.91	1.02	0.50	2.46	0.75
	SDR	0.93	0.90	0.08	2.23	0.83
	Log（1/R）	0.97	0.55	0.68	1.32	1.39
	BD	**0.95**	**0.78**	0.84	**1.20**	**1.53**
Gray-drab soil	REF	0.86	0.89	0.82	2.96	0.68
	FDR	0.93	0.63	0.52	2.08	0.96
	SDR	0.54	2.14	0.29	2.28	0.88
	Log（1/R）	0.97	0.41	0.42	2.46	0.81
	BD	**0.93**	**0.62**	0.92	**1.14**	**1.75**
Total sample	REF	0.87	0.96	0.81	1.38	1.59
	FDR	0.84	1.06	0.82	1.41	1.56
	SDR	0.80	1.20	0.74	1.60	1.38
	Log（1/R）	0.90	0.83	0.85	1.26	1.75
	BD	**0.88**	**0.92**	0.87	**1.20**	**1.83**

According to the table, the results of characteristic band modeling and full band modeling was roughly equal, indicating that after excluding the spectral data the way of leaving a small portion of the spectrum data to model had no effect on the overall precision of inversion of soil total nitrogen composition, but it is more stable, especially the total sample, in which the RPD of the form of four kinds of transformation of REF, FDR, Log (1 / R) and BD is more than 1.40, suggesting that total samples modeling had an ability to roughly estimate soil total nitrogen composition and a relatively stable state of modeling and verification, so the total sample had good precision of model. The accuracy of each soil type was different. In alpine meadow soil, the best inversion index was the Log (1 / R), and the modeling precision was higher, while verification accuracy was general. REF and FDR in alpine grassland soil had good precision and optimal spectrum transform was REF, because of higher, modeling precision and better verification accuracy, making the model on the modeling accuracy and verification accuracy reach the best state at the same time. The best precision in mountain meadow soil was the Log (1 / R), (RDP = 3.08) and the modeling precision was better with verification accuracy reaching a very good state, which can accurately invert soil total nitrogen content of soil type. BD was the best spectral index of Bog soil and the modeling precision was good, as well as verification accuracy reached as a rough estimation of soil total-nitrogen content. In gray-drab soil, only BD reached the standard of RPD which was bigger than 1.40, reaching standard form lessly. The result basically with previous model results of the model is consistent.

2） *Artificial Neural Network Model*

The results of modeling and verification total nitrogen data of BP neural network, using characteristic band spectral data, were shown in Table VI.

TABLE VI. THE RESULTS OF MODELING AND VERIFICATION OF SOIL NITROGEN

Agrotype transformation form optimal scheme			Modeling accuracy		Verification accuracy		
			R^2	RMSE	r	RMSE	RPD
Alpine meadow soil	REF	Scheme 3	0.93	0.63	0.80	1.34	1.60
	FDR	Scheme 2	0.87	0.84	0.80	1.33	1.62
	SDR	Scheme 4	0.94	0.61	0.80	1.43	1.50
	Log（1/R）	**Scheme 3**	**0.95**	**0.50**	**0.82**	**1.23**	**1.75**
	BD	Scheme 3	0.89	0.78	0.81	1.25	1.72
Alpine steppe soil	REF	Scheme 3	0.84	1.04	0.94	1.37	1.03
	FDR	**Scheme 1**	**0.98**	**0.36**	**0.85**	**0.76**	**1.86**
	SDR	Scheme 1	0.91	0.80	0.82	1.37	1.03
	Log（1/R）	Scheme 2	0.88	0.92	0.84	0.80	1.76
	BD	Scheme 2	0.96	0.65	0.85	0.77	1.83
Mountain meadow soil	REF	Scheme 1	0.89	0.62	0.85	0.97	1.88
	FDR	Scheme 2	0.90	0.64	0.92	0.73	2.49
	SDR	Scheme 4	0.90	0.63	0.90	0.83	2.19
	Log（1/R）	Scheme 2	0.93	0.50	0.85	1.10	1.65
	BD	**Scheme 2**	**0.92**	**0.53**	**0.93**	**0.72**	**2.53**
Bog soil	REF	Scheme 2	0.93	0.94	0.94	0.68	2.71
	FDR	Scheme 4	0.95	0.76	0.93	1.71	1.08
	SDR	Scheme 4	0.95	0.77	0.89	0.93	1.98
	Log（1/R）	**Scheme 2**	**0.98**	**0.41**	**0.96**	**0.65**	**2.83**
	BD	Scheme 1	0.96	0.68	0.94	0.87	2.11
Gray-drab soil	REF	Scheme 1	0.83	1.00	0.73	1.15	1.74
	FDR	Scheme 2	0.79	1.11	0.89	0.83	2.41
	SDR	**Scheme 4**	**0.97**	**0.44**	**0.91**	**1.10**	**1.82**
	Log（1/R）	Scheme 4	0.90	0.75	0.92	1.11	1.80
	BD	Scheme 4	0.90	0.75	0.92	1.11	1.80
Total sample	REF	Scheme 1	0.91	0.80	0.84	1.30	1.69
	FDR	Scheme 4	0.94	0.68	0.86	1.26	1.75
	SDR	**Scheme 4**	**0.94**	**0.65**	**0.85**	**1.26**	**1.75**
	Log（1/R）	Scheme 3	0.91	0.81	0.85	1.28	1.72
	BD	Scheme 1	0.90	0.83	0.85	1.27	1.73

DOI 10.5013/IJSSST.a.17.25.15 ISSN: 1473-804x online, 1473-8031 print

From the table VI, the results of characteristic band modeling of the BP neural network was better than the MSLR, manifesting in all the modeling R^2 is more than 0.79. The validation of RPD was more than 1.4 in addition to the three indicators (REF, SDR of alpine steppe soil and FDR of bog soil) and all can satisfy the accuracy demands of a rough estimation, indicating the way of characteristic band modeling to improve the overall accuracy of the model and the ability of the inversion of the model. The best and worst transformation of various soil types was different. The best indicator of alpine meadow soil is Log (1 / R) and the worst was SDR .The best indicator of alpine steppe soil was FDR and the worst was SDR and REF. The best indicator of mountain meadow soil was BD and the worst was Log (1 / R). The best indicator of Bog soil was Log (1 / R) and the worst was FDR. The best indicator of gray-drab soil was SDR and the worst was REF. The best indicator of total samples was the SDR and the worst was Log (1 / R). So, t is not difficult to see that the difference of five kinds of transformation is small in the process of ANN modeling, and there is no particular transformation, which is good or bad and all the indicators are likely to be the best or the worst, which shows a lot of randomness of ANN model and uncertain model results [20].

Choosing characteristic band of modeling method to reduce the input band, shorten the running time of the model and simplify the model, but the accuracy was essentially flat with full band and even slightly better than the full band. After excluding band of low correlation, some soil types of precision has increased, mainly displayed in the verification accuracy, making the model on the accuracy of modeling and validation in sync, which tended to reduce the differences between five types of transformation and various soil types. It shows an invert by using the method of modeling characteristic band of soil total-nitrogen in the study area data to achieve better precision.

V. CONCLUSION

A kind of spectral preprocessing methods(The nine point weighted moving average method), two kinds of model method(MSLR 、 ANN) and five kinds of change(REF、FDR、SDR、Log（1/R）、BD) are used to invert by modeling all band and characteristic bands of high spectral on five types of soil of a soil composition data in the three-river source area. According the above analysis, we get five conclusions. Firstly, the curve characteristic of original spectral reflectance can serve as a reference for using high spectral to recognize the type of soil, e.g. "Bonnet" characteristics of the alpine grassland soil. Secondly, the model of ANN can estimate the total nitrogen content in the soil stably and the model of MSLR, however, whose precision is not better than ANN, is easier to highlight the difference between the soil type and various indexes. Thirdly, modeling with overall sample has better stability and precision of inversion than with different types of soil for that modeling with overall sample is able to estimate roughly total nitrogen composition of soil, which shows a stable model and situation of verification. Fourthly, modeling with characteristic bands is stronger, efficiently than modeling with all bands, to which it has equal precision. Lastly, REF、Log（1/R）and BD is more suitable for linear model, like MSLR, in five different index and differential transformation(FDR, SDR) suits the nonlinear model[21].

This paper focus mainly on the features of f original spectral reflectance, inversion of soil composition with hyper-spectral , model method and ways of modeling(all band and characteristic bands). The later work will concentrate on how to dig relations deeply between soil composition and soil reflectance by choosing different pretreatment method to improve the precision of model and using better model. Trying to use the technology of inverting soil composition with hyper-spectral to solve practical problems is also necessary.

CONFLICT OF INTEREST

The authors confirm that this article content has no conflicts of interest.

ACKNOWLEDGEMENTS

This work was financially supported by Natural Science Foundation（41401397）, Natural Science Foundation of Jiangsu Province(BK20140237), Funded by Key Laboratory of Advanced Engineering Surveying of State Bureau of Surveying and Mapping (201310) .

REFERENCES

[1] Zhang Juanjuan, Tian Yongchao, Yao Xia,ec al. “Estimating Soil Total Nitrogen Content Based on Hyperspectral Analysis Technology”[J]. *Journal of Natural Resources*, 26(5):881-890,2011.

[2] Mondini C, Sequi P. “Implication of soil C sequestration on sustainable agriculture and and environment”[J]. *Waste Management.*(28): 678-684,2008.

[3] Ren Hongyan, Shi Xuezhen, Zhuang Dafang, et al. “Effects on Estimating Soil Total Nitrogen Content and Ratio of Carbon to Nitrogen Using Hyperspectral Reflectance”[J]. *Remote Sensing Technology and Application*,, 27(3): 372-379, 2012.

[4] Zhang Xuelian, Li Xiaona, Wu Juying, Zheng Wei, Huang Qian, Tang Congfeng. “Study on the Determination of Total Nitrogen in Different Types of Soil by Near-Infrared Spectroscopy”[J]. *Spectroscopy and Spectral Analysis*, (4): 906-910, 2010.

[5] Luan Fuming, Zhang Xiaolei, Xiong Heigang, Zhang Fang,Wang Fang. „Comparative Analysis of Soil Matter Content Based on Different Hyperspectral Inversion Models”[J]. *Spectroscopy and Spectral Analysis* ,01:196-200, 2013.

[6] Yu Shikai. “Studies on the Inversion of Soil Organic Matter Content Based on Hyper-spectral”[D].*Chinese academy of agricultural sciences*,2013.

[7] Zhang Juanjuan, Yu Hua, Qiao Hongbo, Ma Xinming, Zhai Qingyun. “Soil organic matter content estimation based on hyperspectral properties”[J]. *Chinese Journal of Eco-Agriculture* ,05:566-572, 2012.

[8] Peng jie, Xiang Hongying, Zhou Qing,ec al. “Prediction on Total Nitrogen Content in Different Type Soils Based on Hyperspectrum”[J]. *Chinese Agricultural Science Bulletin*,29(9): 105-111, 2013.

[9] Viscarra Rossel R A, Webster R. “Predicting soil properties from the Australian soil Visible-near infrared spectroscopic database”[J]. *European Journal of soil Science*.(63): 848-860, 2012.

[10] Wang wei, Shen runping, Ji caoxiang. “Study on Heavy Cu Based on Hyperspectral Remote Sensing” [J]. *Remote Sensing Technology and Application*, (3):348-354, 2011.

[11] Lu yanli, bai youlu, yang liping, et al. “Homogeneity of retrieval model for soil organic matter of different soil types in northeast plain using hyperspectral data”[J]. *Plant nutrition and fertilizer science*,(2): 456-463, 2011.

[12] Wu mingzhu, Li xiaomei, Sha jinming. “Spectral Inversion Models for Prediction of Red Soil Total Nitrogen Content in Subtropical Region” [J]. *Spectroscopy and Spectral Analysis*, 2013, 11:3111-3115, 2013.

[13] Shen Runping, Ding Guoxiang, Wei Guoshuan, Sun Bo. “Retrieval of Soil Organic Matter Content from Hyper-spectrum Based on ANN” [J].*ACTA PEDOLOGICA SINICA*,2009,03:391-397, 2009.

[14] Yuan Zheng, Li Xican, Yu Tao, Zhang Guangbo. “Construction and Innovation on Comprehensive Practice Course of Land-use Remote Sensing Change Detection” [J]. *Science of Surveying and Mapping*,, 05:117-120+164, 2014.

[15] Li. “Study on Prediction of Soil Organic Matter Based on Hyperspectral Remote Sensing” [D]. *Zhejiang University*,2013.

[16] He Junliang, Jiang Jianjun, Zhou Shenglu, Xu Jun, Cai Hailiang, Zhang Chunyao.The “Hyperspectral Characteristics and Retrieval of Soil Organic Matter Content” [J]. *Scientia Agricultura Sinica*,,03:638-64,2007.

[17] He T, Wang J, Lin Z, et al. „Spectral features of soil organic matter” [J]. *Geo-spatial Information Science.*12(1): 33-40, 2009.

[18] Pirie A, Singh B, Islam K. Ultra-Violet, visible, “near-Infrared and mid-infrared diffuse reflectance spectroscopies techniques to predict several soil properties” [J]. *Australian Journal of soil Research*.6(43): 713-72,2005.

[19] Razakamanarivo R H, Grinand C, Razafindrakoto M A. “Mapping organic carbon stocks in eucalyptus plantations of the central highlands of Madagascar: A multiple regression approach” [J].*Geoderma*. 3/4(162): 335-346, 2011.

[20] Chang C W, Laird D A. “Near-Infrared Reflectance Spectroscopy-Principal Components Regression Analyses of Soil Properties” [J]. *Soil Sci Soc Am J*. 2(65): 480-490,2001.

[21] Shepherd K D, Walsh M G. “Development of Reflectance Spectral Libraries for Characterization of Soil Properties” [J]. *Soil Sci Soc Am J*.3(66): 988-998, 2002.