Environ Monit Assess (2015) 187:4130
DOI 10.1007/s10661-014-4130-x

Using hyper-spectral indices to detect soil phosphorus concentration for various land use patterns

Chen Lin · Ronghua Ma · Qing Zhu · Jingtao Li

Received: 16 July 2014 / Accepted: 28 October 2014

Abstract The management of nonpoint source pollution requires accurate information regarding soil phosphorus concentrations for different land use patterns. The use of remotely sensed information provides an important opportunity for such studies, and the previous studies showed that soil phosphorus shows no clear spectral response feature, while the phosphorus concentrations can be indirectly detected from the normalised difference vegetation indices (NDVI). Therefore, this study uses an optimised index in the RED and near-infrared (NIR) wavelengths to estimate total phosphorus and Olsen-P concentrations. The prediction accuracy is not entirely satisfactory with respect to a mixed land use dataset in which the determination coefficient was maintained at approximately 0.6, with particularly poor performance obtained for forest land group. However, the prediction accuracy increases markedly with the separation of samples into broad land use categories, even the R^2 was exceeded 0.8 for tea plantation group. The soil phosphorus prediction effect showed obvious variance for different land use patterns, which was related to vegetation growth conditions and critical soil properties including soil organic matter and mechanical composition.

Keywords Hyper-spectral · Vegetation indices · Land use · Soil phosphorus

Submitted to: Environmental Monitoring and Assessment

C. Lin (✉) · R. Ma · Q. Zhu
State Key Laboratory of Lake Science and Environment, Nanjing Institute of Geography and Limnology, Chinese Academy of Sciences, Nanjing 210008, China
e-mail: clin@niglas.ac.cn

C. Lin
The Key Laboratory of the Coastal Zone Exploitation and Protection, Ministry of Land and Resource, Nanjing 210008, China

C. Lin
State Key Laboratory of Soil and Sustainable Agriculture, Institute of Soil Science, Chinese Academy of Sciences, Nanjing 210008, China

J. Li
School of Geographic and Oceanographic Sciences, Nanjing University, Nanjing 210093, China

Introduction

The concentration of total phosphorus is a fundamental characteristic to understand the biological and chemical properties of soil. The accumulation of phosphorus in soils is one of the major challenges to catchment management globally. Phosphorus fertiliser has led to improved agricultural production in many areas of the world. However, phosphorus runoff from agricultural areas is a key agricultural nonpoint source (NPS) driving the eutrophication of freshwater and coastal ecosystems. The estimation of the spatial and temporal distribution of the soil phosphorus concentrations for different land use patterns would have significant benefits (Yang et al. 2012)

Traditional determination of soil phosphorus concentrations require extensive field sampling and laboratory

Published online: 15 November 2014

analysis, which is cost and labour intensive. Remote sensing using hyper-spectral sensors has the advantage of being able to efficiently and rapidly capture information regarding soil components based on their spectral features. These approaches have become important to the estimation of some soil properties (McCarty et al. 2002; Viscarra Rossel et al. 2006). Soil characteristics (e.g. moisture and organic matter) can be directly estimated (Vasques et al. 2008), while other properties can be inferred by statistical relationships between the aboveground and belowground characteristics of the land cover. The use of hyper-spectral data to estimate soil phosphorus concentrations is yet to be successful, with determination coefficients rarely above 0.6 (Hu 2013). This has resulted from the multiple forms that phosphorus can take in the soil as phosphates of Ca, Mg and Al. Furthermore, these forms of phosphorus have no clear spectral features in most soils, which prevent them from being directly detected by optical means. Sridhar Maruthi et al. (2009) showed that an increase in soil phosphorus may cause a decrease in soil reflectance, with absorption peaks around 1122, 1374 and 1439 nm. These peaks were related to the presence of Mg and P hydrate and Ca and P hydrate.

Vegetation growth status can be directly detected by remote sensing using standard vegetation indices such as the normalised difference vegetation indices (NDVI). Vegetation status is not only closely related to soil fertility but it is also sensitive to the concentrations of soil nutrients. Numata et al. (2003) showed that the soil phosphorus exhibited a correlation with remotely sensed measures such as the NDVI as well as the spectral principal component variables determined using a tasseled cap transformation. Rivero et al. (2009) developed the statistical relationships between spectral signatures of vegetation and soil phosphorus in surface horizons. These studies showed that soil phosphorus can be indirectly estimated using reflectance data in the near-infrared (NIR) and RED wavebands. It follows that an increase in spectral resolution, using hyper-spectral sensors, would increase the possibility to indirectly estimate soil properties (Daughtry et al. 2000). Kawamura et al. (2011) used the hyper-spectral reflectance based on vegetation indices (VIs) to determine the phosphorus content in soils. Their use of the normalised difference spectral index (NDSI), based on the centre wavelengths of each spectral region, showed that the NDSI, using wavelengths in mid visible (R_{523}, R_{583}), gave the best result (R^2=0.76).

While the use of vegetation indices was shown to be feasible, there are several problems that have yet to be addressed. First, NDVI indices based on the centre wavelengths of RED and NIR wavebands were selected without optimising for specific wavelengths using focused field research. Second, specific soil types and land use type were considered separately, and little information is available regarding the accuracies related to different land use patterns.

The objectives of this study were 1) to detect the spectral response of soils with different phosphorus content under various land use patterns, 2) to optimise a hyper-spectral NDVI index to estimate concentrations of soil total phosphorus (TP) and Olsen-P and 3) to compare soil phosphorus predictive accuracy of different spectral indices under different land uses.

Material and methods

Study site and soil sampling

The field work was conducted in the counties of Donba and Yaxi, which are affiliated to Gaochun City, in the Ecological Reserve of the Taihu Lake basin. This area of China is characterised by high economic development with elevated agricultural NPS pollution and lake eutrophication. The two counties were designated as land consolidation demonstration zones. Agriculture is the dominant land use, but has gone through major changes over the past 20 years. More intensive agricultural activities are now common, often replacing areas where native forest land and traditional farmland were once present.

A total of 105 topsoil layer samples were collected (0–0.1 m depth) in late October 2012 from agricultural and nonagricultural areas. The samples were classified into three groups based on the surrounding land use (Fig. 1): forestland (FL), paddy and dry land (PDL) and tea plantation (TPT). Each group contained 35 samples.

The soil samples were collected in regions of Alfisols and Histic soils to reduce the influence of different soil types on the spectral response. Soils were sampled nine times within a radius of 20 m from the sample plot centre and were then mixed into a single sample. The sampling sites were 150 to 200 m apart (using a global positioning system) to ensure the spatial uniformity (Fig. 2).

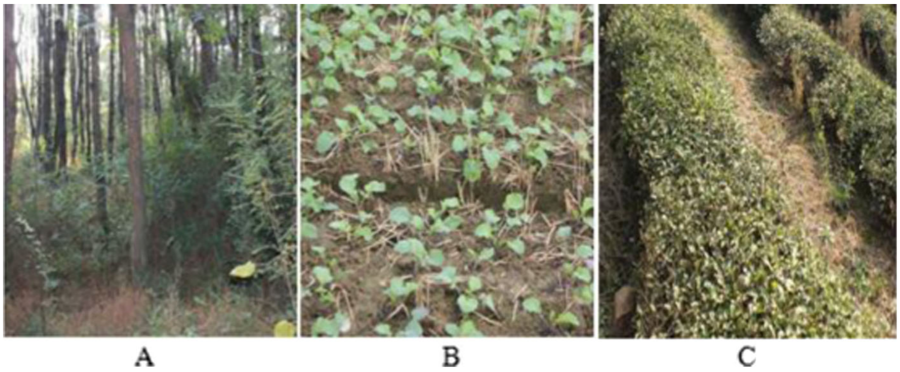
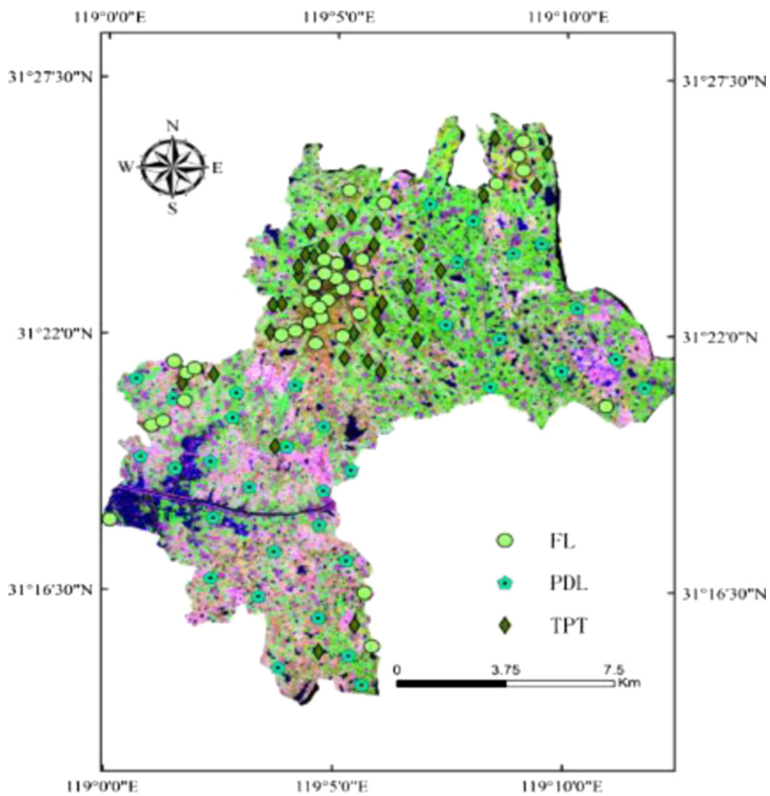


Fig. 1 Field sample photos of different land use types in the study area. **a** FL, **b** PDL, **c** TPT

Soil chemical analysis

Soil samples were air-dried and grinded prior to chemical analysis. Portions of the soil samples were digested with HNO_3–HF–$HClO_4$, and TP concentrations were measured with inductively coupled plasma-atomic emission spectrometry (ICP-AES) (Lin et al. 2008). Olsen-P—as available phosphorous—was measured using the Olsen test, where 1 g air-dried soil (sieved <2 mm) was shaken in 20 ml 1 M NaHCO3 (sodium hydrogen carbonate, pH 8.5) for 30 min (Olsen et al. 2002). The soil organic matter (SOM) of each sample was determined after oxidation by potassium bichromate and a sulphuric acid solution and measured by an external heating method (Houba et al. 1989). The contents of sand (0.05 to 2 mm), silt (0.002 to 0.05 mm) and clay (0 to 0.002 mm) particles in soil were measured following the pipette method (Soil Science Society of China 2000).

Fig. 2 Map of study area and sampling location



Measurement of spectral reflectance

Soil reflectance spectra were obtained with an ASD FieldSpec Pro Portable Spectrometer (Analytical Spectral Devices, Boulder, CO, USA). The measurements were performed in a dark room, and soil was set in a Petri dish for consistent control of irradiance conditions. To eliminate the influence of soil water content on the spectral curves, the samples were air-dried for 10 days before the spectral measurements were obtained. A 1000-W halogen lamp situated at 0.70 m from the soil sample provided near-collimated rays over the sample area. The zenith angle of the lamp was set to 30°. This particular configuration was chosen to limit the influence of soil roughness by minimising the fraction of shadow. For each sample, reflectance measurements were acquired from 350 to 2500 nm with a spectral resolution of 1.4 nm, and four spectra were obtained over the central area of the sample after rotating the Petri dish 90° each time. All spectra data were visually checked and averaged by using RS2 for windows software (ASD, Boulder, CO, USA) and then exported to Unscrambler™ (Liu et al. 2009). In the pre-processing phase, spectral data in several wavelength regions were eliminated because of a low signal-to-noise ratio (350 to 399 nm and 2450–2500 nm), leaving a total of 2051 spectral bands (400 to 2450 nm). The reflectance data were smoothed with Unscrambler™ using the Savitzky–Golay method to reduce the noise.

Modeling

The four traditional vegetation spectral indices were explored (Table 1).

To improve the assessment, response wavelengths in the red and NIR band against TP and Olsen-P were examined to identify an optimal combination of wavelengths, rather than following the traditional approach of using the centre wavelength. A first-derivative analysis was used to highlight the spectral absorption features of soil properties with respect to the logarithm of soil phosphorus. Principal component analysis (PCA) was used to determine the wavelength range in the red and NIR spectral region which provided the most information on soil phosphorus for each land use pattern. The correlation coefficients between the TP and Olsen-P contents and the spectral reflectance of each wavelength in red and NIR regions was used to compare fitting values.

The samples were randomly divided into index development (75) and validation (25) datasets. A spectral index in the form of an optimised NDVI was used to model TP and Olsen-P concentrations. The coefficient of determination R^2 was used to test the stability, while the root mean square error (RMSE) was used to test the capacity (Kooistra et al. 2001). In addition to the relationship between prediction accuracy of soil P by spectral indices and the vegetation growth condition, the actual NDVI value of each sample plot was extracted from Landsat Thematic Mapper (TM) data from November 5, 2012, the closest date to the actual sampling period.

Two scenarios were considered respectively during the modeling process, one considering individual different land uses separately and one where all the samples were combined.

Table 1 Traditional vegetation spectral indices used to predict soil phosphorus

Spectral indices	Equation	Reference
NDVI	$(R_{830}-R_{660})/(R_{830}+R_{660})$	Rouse et al. (1974)
$NDVI_{green}$	$(R_{830}-R_{550})/(R_{830}+R_{550})$	Gitelson et al. (1996)
GRI	R_{830}/R_{550}	Inoue et al. (1998)
NDSI	$0.89\times f_{(R523,R583)} + 0.05$	Kawamura et al. (2011)

Results

Soil properties

Soil phosphorus concentrations as TP and Olsen-P, SOM and soil particle composition showed a range of values across the different land uses (Table 2).

In general, the soil characteristics differed between land use patterns as: i) TP concentrations were lowest in the TPT group, while TP values of the PDL group were similar to the FL group. ii) The FL group had the lowest Olsen-P, where the ratio between Olsen-P and TP was also the lowest at 2.8 %. iii) SOM was highest in FL and lowest in TPT. The SOM concentrations exceed the soil phosphorus content in the whole sample set, indicating that surface soil was comprised mainly organic matter. iv) The soil particle composition in the three groups follows the tendency that clay (%)<sand (%)<silt (%) with no significant difference between groups.

Table 2 Selected soil properties of samples from land uses

Group	Items	TP ($g\ kg^{-1}$)	Olsen-P ($g\ kg^{-1}$)	SOM ($g\ kg^{-1}$)	Sand (%) (0.05 to 2 mm)	Silt (%) (0.002 to 0.05 mm)	Clay (%) (0 to 0.002 mm)
Forestland (FL)	Min	0.235	0.0075	0.85	6.23	50.9	5.18
	Max	0.930	0.0348	4.48	40.87	85.9	18.9
	Mean	0.53	0.015	2.88	19.1	71.45	9.14
	SD	0.347	0.006	0.806	0.883	0.411	0.478
Paddy and dry land (PDL)	Min	0.186	0.0089	0.72	7.1	50.4	5.48
	Max	0.932	0.0578	3.91	37.73	74.8	17.7
	Mean	0.493	0.024	1.99	19.78	64.01	9.19
	SD	0.636	0.004	0.544	0.676	0.303	0.378
Tea plantation (TPT)	Min	0.157	0.0086	0.69	10.01	52.4	4.49
	Max	0.804	0.0488	3.42	55.42	70.9	17.6
	Mean	0.399	0.019	1.54	23.25	60.6	9.18
	SD	0.155	0.004	0.765	0.682	0.293	0.462

SD Standard Deviation

Spectral properties

To make an initial differentiation between the spectral characteristics of three land use groups, the curves showing the mean reflectance data were used (Fig. 3).

The reflectance of TPT is greater throughout the NIR and also in the visible wavelengths. Several successive small absorption features are also seen between 1100 to 1400 nm, which are generally consistent with the absorption features of Al-bound P, Mg-bound P and Ca-bound P. Mean spectra from the PDL and FL land uses were similar up to 1400 nm. There was a small difference between the mean spectra from these groups in the 800 to 900 nm range, which is likely to be associated to SOM.

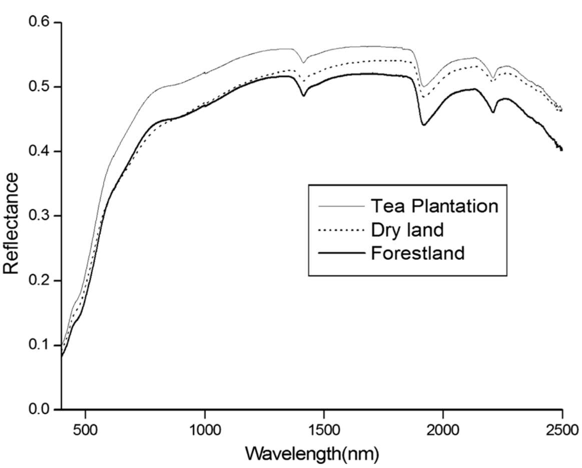


Fig. 3 Average reflectance spectral data for each soil group

Predicting soil phosphorus using spectral indices

Soil TP and Olsen-P were predicted by spectral data using the whole dataset and separately on the basis of three land use groups.

Soil phosphorus accuracy for the whole dataset

With respect to the whole dataset (all samples regardless of land-use), the logarithms of TP and Olsen-P concentrations were compared with the first-derivative of spectral reflectance. The correlation coefficients had high oscillations due to minor differences in the original reflectance spectra, but showed a clear trend, which was similar for both TP and Olsen-P (Fig. 4).

The optimal response was determined in both the red spectral region (630 to 690 nm) and NIR spectral region (690 to 1550 nm) as the best fitting wavelength at 695 nm with TP (r=0.76) and 693 nm with Olsen-P (r=0.74). In the NIR, the optimum-fitting wavelength was 1440 to 1453 nm for TP and 1079 to 1090 nm for Olsen-P. Both regions are consistent with the absorption peaks generated by phosphate bound with Al and Mg (Sridhar Maruthi et al. 2009). However, the highest correlation coefficient with Olsen-P did not exceed 0.75 in the whole NIR region.

The wavelengths with the best correlation coefficient in each spectral region were selected for TP and Olsen-P estimation NDVI indices without considering

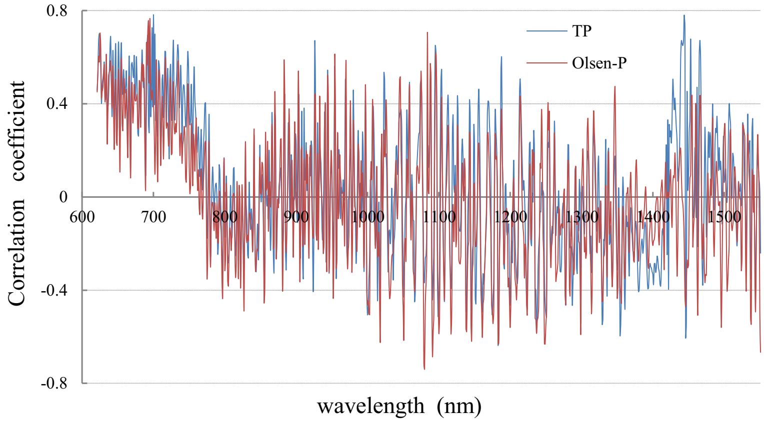


Fig. 4 Correlation coefficients between the logarithm of soil phosphorus and first-derivative reflectance data (630 to 1550 nm)

differences in land use. Validation of the equations showed similar results (Table 3).

It can be seen from Table 3 that R^2 for TP and Olsen-P was approximately 0.6, and the R^2 for the validation dataset was near 0.5 for both phosphorus soil parameters, with an RMSE around 1. Models from past studies (Table 1) were also explored (Table 4).

The modeling effects obtained with three previous indices were not ideal, while the NDSI provide similar or better (for Olsen-P) results with respect to the optimised NDVI method.

Soil phosphorus accuracy for separate land use patterns

The analysis of individual land use groups provide a much improved relationship between the measured soil phosphorus and predicted soil phosphorus and the optimised index (Fig. 5).

The improvement was most significant for TPL and PDL groups, with R^2 for the TPT group exceeded 0.82 for TP and Olsen-P, and with a root mean square error rate (RMSE) less than 0.1. The FL group showed a very poor fitting effect between measured and modeled soil phosphorus for both TP and Olsen-P in which the R^2 were 0.21 and 0.11, respectively.

Discussion

We used an optimised NDVI spectral index, with hyper-spectral data to estimate soil phosphorus conditions in mixed and single land use conditions. The results indicated that the approach was not ideal for mixed land use groups. A significant improvement was made when land use groups were considered separately. We explored the relationship between factors that might influence the improvement due to land use, in particular the conditions of vegetation and soil.

Vegetation growth conditions

Soil phosphorus influences vegetation tissue composition, as well as being one of the components of nucleic acids and enzymes. In particular, Olsen-P plays a critical role on plant growth (Mutanga et al. 2004; Ferwerda and Skidmore 2007). We applied a standard NDVI approach with multi-spectral data from Landsat Thematic Mapper (TM) to estimate surface growth condition of the study plots (Rivero et al. 2009; Kawamura et al. 2011). The measured NDVI and the surface vegetation growth condition showed the best correlation for the forest land use group (FL) (Table 5).

Table 3 Statistical data of modeling results between spectral indices and soil phosphorus

	Equation	Calculation R^2	Calculation RMSE	Verification R^2	Verification RMSE
TP	$y=-0.213\times\ln((r'_{1444}-r'_{695})/((r'_{1444}+r'_{695}))+2.865$	0.63	0.87	0.48	1.12
Olsen-P	$y=-0.4\times\ln((r'_{1079}-r'_{693})/((r'_{1079}+r'_{693}))+1.092$	0.61	0.45	0.50	0.98

Table 4 Statistical data of modeling results using other traditional indices

Spectral indices	TP		Olsen-P	
	R^2	RMSE	R^2	RMSE
NDVI	0.35	1.42	0.38	0.98
$NDVI_{green}$	0.32	1.13	0.22	1.44
GRI	0.27	2.03	0.47	1.98
NDSI	0.58	0.78	0.63	0.73

In general, the mean value of NDVI was similar among the three groups; nevertheless, the value in TPT group was slightly higher than in the other two groups. However, the cv value differed notably among different groups, with the highest value for the FL group (26.7 %) and the lowest was appeared for the TPT group (12.2 %), while it is opposite to the prediction results shown in Fig. 4. The higher cv value reflected the high inhomogeneity of vegetation patterns and growth conditions of each group. The forestland in this study had complete ecological structures and mixed plants, including surface grass and bushes, in addition to primary and secondary forests trees including Bamboo and Masson pine. The FL sites exhibited the highest plant diversity of the three groups, which was directly reflected in the cv value. Likewise, there were several cropping patterns including rice, wheat and coal, which existed in the PDL sites, demonstrated by post-harvesting crop residues present during the sampling. However, the plant species was more uniform in the TPL and these were more uniformly cropped, which led to the lowest cv value for NDVI values and the best soil phosphorus prediction accuracy. The influence of species diversity and cropping uniformity will therefore have an important impact on the remote analysis of soil phosphorus conditions.

Soil properties

The study area soil types were Alfisols and Histic, both of which commonly have organic matter in the top soil. The mechanical composition was dominated by silt, whose percentage was higher than 75 % (Gong et al. 2003). SOM and soil mechanical composition exhibited clear relationships with land use patterns. This is most likely due to agricultural practices, in particular the loss of soil material due to soil erosion and the modification of natural nutrient conditions due to the application of fertilisers.

From the land use surveys taken at the time of sampling and the analysis of historic land use/land cover data, much of the farmland and tea plantation area sampled in this study were previously primary forest, with the arable land being created over the past 10 years. A study of phosphate and nitrogen fertiliser use indicated that P_2O_5, $Ca_3 (PO_4)_2$ and $CO (NH_2)_2$ were applied during the cultivation process, both on TPL and PDL areas. Fertiliser was more necessary on the tea plantations to assist the absorption of tea leaves (N, 18 kg a; P, 10 kg a). In contrast, the forest land mainly comprised primary and partial secondary forests, which were planted at least 30 years prior. Therefore, the forest land soil has a lower possibility to receive fertiliser and was less affected by anthropogenic impacts. The resultant soil properties and mechanical composition of the FL group was significantly different with respect to PDL and TPT. The widespread application of fertiliser would make the soil phosphorus concentrations, specifically, the Olsen-P increase over time (Qin et al. 2007; Motavalli and Miles 2002). Soil erodibility would also increase which would lead to soil element loss when the element concentration degree exceeds the soil saturation capacity (Michel and Pedro 1996).

Soil erosion is closely related to soil mechanical composition (Zhang et al. 2003; Zou et al. 2008). The silt proportion is expected to exceed 75 % in Alfisols and Histic soils. The sand proportion increases with the erosion intensity as the tiny particles are prone to be displaced and the surface soil simultaneously is expected to be rougher (Monlgomery et al. 1997; Luleva et al. 2011). Despite the proportion of silt being higher than that of sand for the three groups, the lowest proportion of silt and highest proportion of sand were observed in the TPT group (Table 2), indicating the severest erosion intensity. The field survey confirmed that moderate erosion occurred on the tea plantation and in partially arable land. During the erosion process, particulate TP would be released during the runoff (Wang et al. 2012). The mean TP concentrations were lowest for TPT and highest for FL. Additionally, the standard deviation of TP in PDL was higher than in TPT, indicating that the extent of the TP loss was more variable in PDL areas.

It is widely acknowledged that SOM significantly affects the spectral reflectance throughout the visible and particularly in the NIR region. SOM influences the spectral characteristics of other soil properties, which

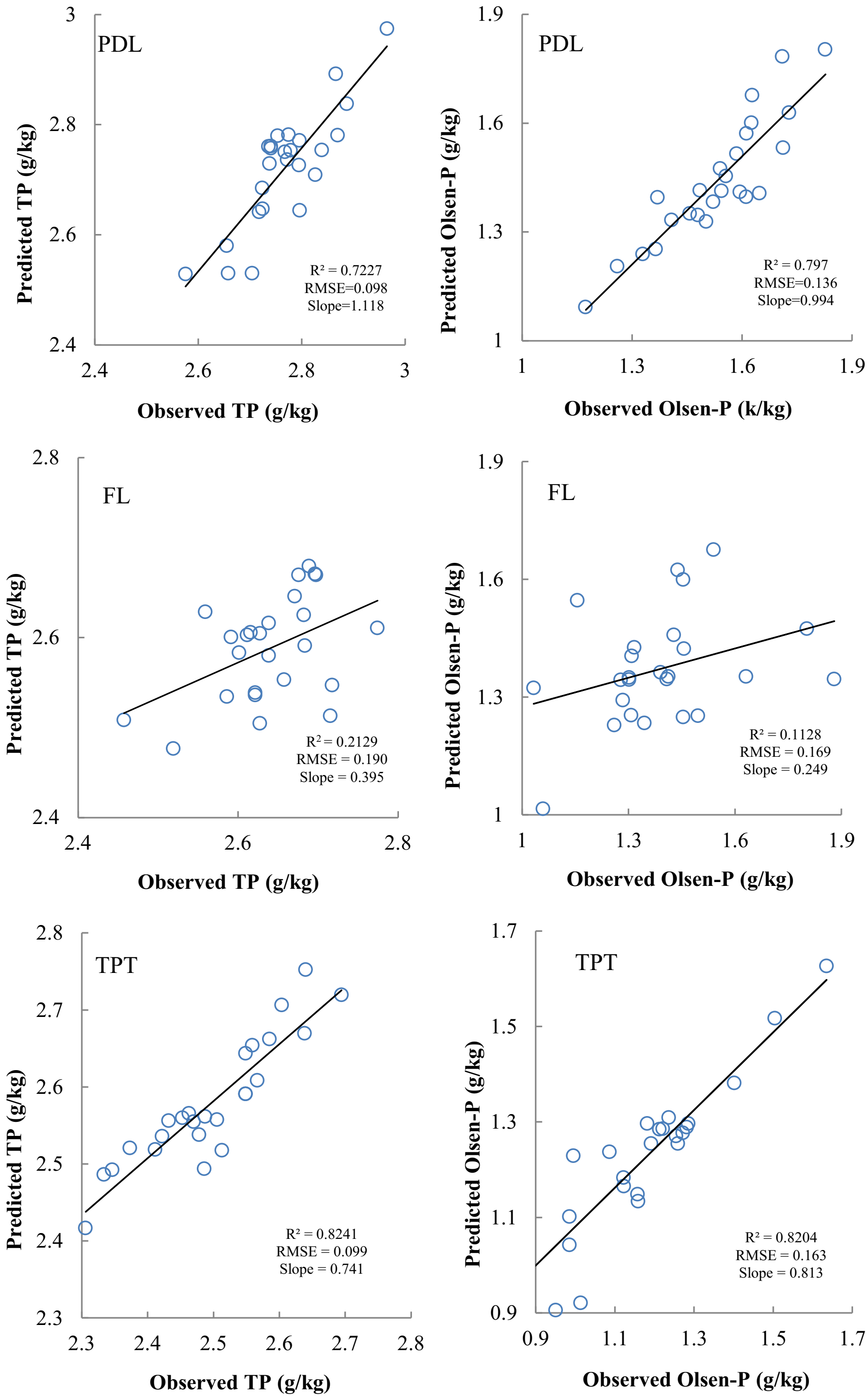


Fig. 5 Relation between predicted and observed TP/Olsen P for different land use patterns

lead to a decreased prediction accuracy (Ben-dor et al. 1997). Therefore, the differences in the soil phosphorus prediction accuracy among the three groups may also be related to differences in SOM concentration. SOM, like soil phosphorus, is strongly influenced by land use, which was confirmed in this study, given that the mean

Table 5 Description of plant growth and NDVI in each group

Group	Description	NDVI			
		Max	Min	Mean	$CV_{\%}$
TPT	Tea	0.656	0.456	0.526	12.2
PDL	Rice and wheat/rice and cole	0.662	0.367	0.475	16.5
FL	Primary forests; secondary forests, mainly with bamboo, Masson pine	0.620	0.259	0.484	26.7

SOM concentration in FL was the highest among the three groups. PDL had a slightly higher average SOM concentration than TPT (Table 2). It should be noted that the concentration SOM for different land use patterns was negatively correlated to the soil phosphorus prediction accuracy (Table 2 and Fig. 5), which confirms the hypothesis that high concentrations of SOM limit the use of spectral characteristics to monitor soil phosphorus conditions.

The spectral characteristics of the soil mechanical composition were most evident in the visible region. Such changes would have little impact on indices based on reflectance measurements in red and NIR regions. However, the mechanical composition is strongly linked to soil erodibility and, therefore, has a strong indirect influence on the variations in the concentrations of SOM and phosphorus.

Conclusion

Identifying the optimal response wavelength in the RED and NIR wavelengths improved the use of NDVI to predict the soil TP and Olsen-P concentrations with respect to the standard NDVI approach. This optimized NDVI provided better results than most other indices and comparable results with respect to NDSI. However, the predictive capacity of this index was significantly improved when land use was also considered. Prediction accuracy was superior to 70 % (R^2) and 80 % for cultivated land cover of PDL and TPT, respectively.

The poor result for the FL areas was associated to the higher variance in vegetation growth conditions and the increased impact of SOM on soil spectral properties. In land use groups, with more uniform species and spatial arrangement, the accuracy of soil surface phosphorus prediction was improved. The mechanical composition of the soil indirectly affects the spectral sensitivity of different soil phosphorus concentrations due to changes in the proportion of silt and sand and their impact on soil erodibility.

Further analyses should focus on extending this optimisation approach to other land use types. As the availability of hyper-spectral data increases, so will our capacity to monitor changes in soil characteristics in areas of managed land cover.

Acknowledgments Financial supports were provided by The National Natural Science Foundation of China (Grant No. 41301227) and Research Fund of Key Laboratory of Coastal Zone Exploitation and Protection, Ministry of Land and Resource (2013CZEPK06) and Research Fund of State Key Laboratory of Soil and Sustainable Agriculture, Nanjing Institute of Soil Science, Chinese Academy of Science (Y412201427). Data were supported by Scientific Data Sharing Platform for Lake and Watershed, Nanjing Institute of Geography and Limnology, Chinese Academy of Sciences

References

Ben-Dor, E., Inbar, Y., & Chen, Y. (1997). The reflectance spectra of organic matter in the visible near-infrared and short wave infrared region (400–2500 nm) during a controlled decomposition process. *Remote Sensing of Environment, 61*(1), 1–15.

Daughtry, C. S., Walthall, C. L., Kim, M. S., Brown, D. C. E., & McMurtrey, J. E. (2000). Estimating corn leaf chlorophyll concentration from leaf and canopy reflectance. *Remote Sensing of Environment, 74*, 229–239.

Ferwerda, J. G., & Skidmore, A. K. (2007). Can nutrient status of four woody plant species be predicted using field spectrometry? *ISPRS Journal of Photogrammetry and Remote Sensing, 62*, 406–414.

Gitelson, A., Kaufman, Y. J., & Merzlyak, M. N. (1996). Use of a green channel in remote sensing of global vegetation from EOD-MODIS. *Remote Sensing of Environment, 58*, 289–298.

Gong, Z. T., Chen, Z. C., & Zhang, G. L. (2003). World reference base for soil resources (WRB): establishment and development. *Soils, 35*(4), 271–278.

Houba, V. J. G., Van der Lee, J. J., Novozamsky, I., & Walinga, I. (1989). *Soil and plant analysis, a series of syllabi: part 5. Soil analysis procedures*. The Netherlands: Wageningen Agricultural University.

Hu, X. Y. (2013). Application of visible/near-infrared spectra in modeling of soil total phosphorus. *Pedosphere, 23*(4), 417–421.

Inoue, Y., Moran, M. S., & Horie, T. (1998). Analysis of spectral measurements in paddy field for predicting rice growth and yield based on a simple crop simulation model. *Plant Production Science, 1*, 269–279.

Kawamura, K., Mackay, A. D., Tuohy, M. P., Betteridge, K., Sanches, I. D., & Inoue, Y. (2011). Potential for spectral indices to remotely sense phosphorus and potassium content of legume-based pasture as a means of assessing soil phosphorus and potassium fertility status. *International Journal of Remote Sensing, 32*(1), 103–124.

Kooistra, L., Wehrens, R., Leuven, R. S. E. W., & Buydens, L. M. C. (2001). Possibilities of visible-near-infrared spectroscopy for the assessment of soil contamination in river floodplains. *Analytica Chimica Acta, 446*, 97–105.

Lin, C., He, M. C., Zhou, Y. X., Guo, W., & Yang, Z. F. (2008). Distribution and contamination assessment of heavy metals in sediment of the Second Songhua River China. *Environmental Monitoring and Assessment, 137*, 329–342.

Liu, H. J., Zhang, Y. Z., & Zhang, B. (2009). Novel hyperspectral reflectance models for estimating black-soil organic matter in Northeast China. *Environmental Monitoring and Assessment, 154*, 147–154.

Luleva, M. I., Werff, H. V. D., Jetten, V., & Meer, F. V. D. (2011). Can infrared spectroscopy be used to measure change in potassium nitrate concentration as a proxy for soil particle movement? *Sensors, 11*, 4188–4206.

McCarty, G. W., Reeves, J. B., III, Reeves, V. B., Follett, R. F., & Kimble, J. M. (2002). Mid-infrared and near-infrared diffuse reflectance spectroscopy for soil carbon measurement. *Soil Science Society of America Journal, 66*, 640–646.

Michel, A. B., & Pedro, A. S. (1996). Soil phosphorus movement and budget after 13 years of fertilized cultivat ion in the Amazon basin. *Plant and Soil, 184*(1), 23–31.

Monlgomery, J. A., Busacia, A. J., & Frazier, B. E. (1997). Evaluating soil movement using cesium 137 and revised universal soil loss equation. *Soil Science Society of America Journal, 61*(2), 571–579.

Motavalli, P., & Miles, R. (2002). Soil phosphorus fractions after 111 years of animal manure and fertilizer applications. *Biology and Fertility of Soils, 36*(1), 35–42.

Mutanga, O., Skidmore, A. K., & Prins, H. H. T. (2004). Predicting in situ pasture quality in the Kruger National Park, South Africa, using continuum-removed absorption features. *Remote Sensing of Environment, 89*, 393–408.

Numata, I., Soares, J. V., Leonidas, D. A., Roberts, F. C., Chadwick, O. A., & Batista, G. T. (2003). Relationships among soil fertility dynamics and remotely sensed measures across pasture chronosequences in Rondônia, Brazil. *Remote Sensing of Environment, 87*, 446–455.

Olsen, S. R., Schepers, J. S., Francis, D. D., & Schlemmer, M. R. (2002). Detection of phosphorus and nitrogen deficiencies in corn using spectral radiance measurements. *Agronomy Journal, 94*, 1215–1221.

Qin, S. J., Liu, J. S., Wang, G. P., & Zhou, W. M. (2007). Phosphorus fractions under different land uses in Sanjiang Plain. *Environmental Sciences, 28*(12), 2777–2782 (in Chinese).

Rivero, R. G., Grunwald, B. M. W., & Osborne, T. Z. (2009). Integrating spectral indices into prediction models of soil phosphorus in a subtropical wetland. *Remote Sensing of Environment, 113*, 2389–2402.

Rouse, J. W., Hass, R. H., Schell, J. A., Deering, D. W., & Harlan, J. C. (1974). *Monitoring the vernal advancements and retro gradation of natural vegetation*. Greenbelt: NASA/GSFC Final Report.

Soil Science Society of China. (2000). *Methods of soil agrochemistry analysis*. Beijing: Chinese Agriculture Science and Technology Press (in Chinese).

Sridhar Maruthi, B. B., Vincent, R. K., Witter, J. D., & Spongberg, A. L. (2009). Mapping the total phosphorus concentration of biosolid amended surface soils using LANDSAT TM data. *Science of the Total Environment, 407*(8), 2894–2899.

Vasques, G. M., Grunwald, S., & Sickman, J. Q. (2008). Comparison of multivariate methods for inferential modeling of soil carbon using visible/near-infrared spectra. *Geoderma, 146*, 14–25.

Viscarra Rossel, R. A., Walvoort, D. J. J., McBratney, A. B., Janik, L. J., & Skjemstad, J. O. (2006). Visible, near infrared, mid infrared or combined diffuse reflectance spectroscopy for simultaneous assessment of various soil properties. *Geoderma, 131*, 59–75.

Wang, W. J., Cheng, H. G., Hao, F. H., Ouyang, W., Liu, S. Q., & Lin, C. Y. (2012). The influence of land-use change on the forms of phosphorus in soil profiles from the Sanjiang Plain of China. *Geoderma, 189*, 207–214.

Yang, W. J., Cheng, H. G., Hao, F. H., Ouyang, W., Liu, S. Q., & Lin, C. Y. (2012). The influence of land-use change on the forms of phosphorus in soil profiles from the Sanjiang Plain of China. *Geoderma, 189*, 207–214.

Zhang, Y., Zhang, H., Peng, B. Z., & Yang, H. (2003). Soil erosion and nutrient loss of various land use patterns. *Bulletin of Soil and Water Conservation, 23*(1), 23–31 (in Chinese).

Zou, C., Xu, F. L., & Yan, Y. D. (2008). The analysis of soil mechanical composition and available nutrient under different land uses patterns in the loess Hilly Gully Region. *Chinese Agricultural Science Bulletin, 24*(12), 424–427 (in Chinese).