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# Prediction of soil content using near-infrared spectroscopy

**Yong He and Haiyan Song**

*Near-infrared spectroscopy can be used to accurately predict certain soil properties, making it a valuable tool in precision farming.*

Modern technological developments in positioning, sensing, and control systems have opened a new era in which many traditional agricultural practices are being left behind. Replacing them are 'precision farming' techniques that manage variability within a field by applying agronomic inputs in the right place, at the right time, and in the right quantity to reduce the environmental impact of crop production. Visible and near-infrared (NIR) spectroscopy has emerged as one of these techniques, enabling the rapid and nondestructive analytical correlation of diffusely reflected NIR radiation with chemical and physical properties of soil components.

NIR spectroscopy has been used for assessing grain and soil qualities[1–5] and has proven to be a rapid, convenient means of analyzing many soil constituents at the same time. The goals of this study were to analyze the potential of NIR spectroscopy to estimate soil nitrogen content (N), phosphorus content (P), potassium content (K), organic matter content (OM), and pH and to combine these predictions with geographic information systems (GIS).

The site where we performed our experiments is located in Hangzhou, China. The soil type was classified as loamy mixed active thermic aeric endoqualf according to Zhejiang soil classification.[6] The test field boundary was defined using a Trimble AgGPS 132 global positioning system receiver. A total of 165 soil samples were collected at a depth of 20 centimeters, then divided into two groups. Group A was tested for N, P, K, OM, and pH using traditional methods; group B was analyzed with a visible and NIR spectrometer (ASD, 350-2500nm). Group B samples were air dried and sieved with a 2mm sieve, then set in petri dishes. Reflectance spectra were taken over the central area of each dish, recoded and checked visually, then averaged and exported to the multivariate analysis software (The Unscrambler 8.0). Representative mean absorbance (log 1/R) soil spectra of 10 samples are shown in Figure 1.

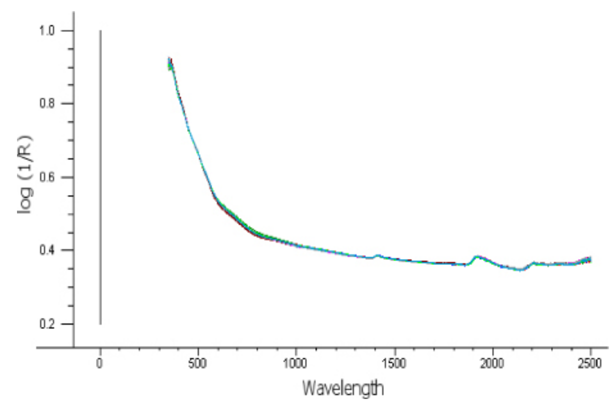


***Figure 1.*** *Representative mean absorbance soil spectra of 10 samples.*

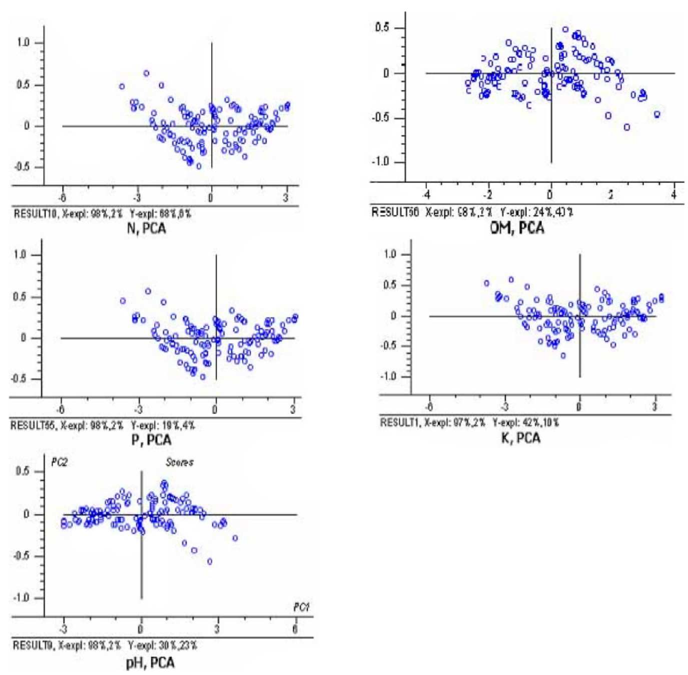


***Figure 2.*** *Score plot of the 135 samples on the first two principal components.*

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***Table 1.** Calibration statistics for N, P, K, OM and pH*

| | | | | Calibration | | | | Cross-validation | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Soil constituent | Gap sizes | Method | F | r | SEC | RMSEC | bias | r | SECV | RMSECV | bias |
| N | 9 | PLS | 7 | 0.967 | 2.055 | 2.048 | $1.97e^{-6}$ | 0.938 | 2.829 | 2.819 | 0.021 |
| OM | 11 | PLS | 5 | 0.962 | 0.058 | 0.058 | $-6.79e^{-8}$ | 0.957 | 0.061 | 0.061 | $-0.9e^{-3}$ |
| P | 9 | PLS | 6 | 0.651 | 26.64 | 26.31 | $1.79e^{-7}$ | 0.543 | 29.54 | 29.43 | -0.25 |
| K | 9 | PLS | 6 | 0.78 | 31.07 | 30.95 | $-3.34e^{-6}$ | 0.763 | 32.11 | 32.98 | -0.15 |
| pH | 9 | PLS | 3 | 0.935 | 0.064 | 0.063 | $-2.47e^{-8}$ | 0.931 | 0.06 | 0.065 | $-2.87e^{-4}$ |

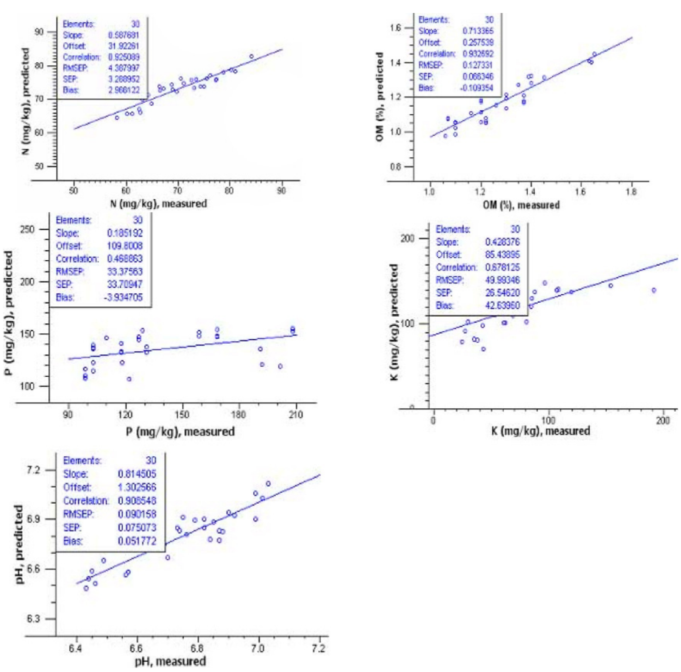


***Figure 3.** Correlation between measured and predicted values of N, P, K, OM, and pH.*

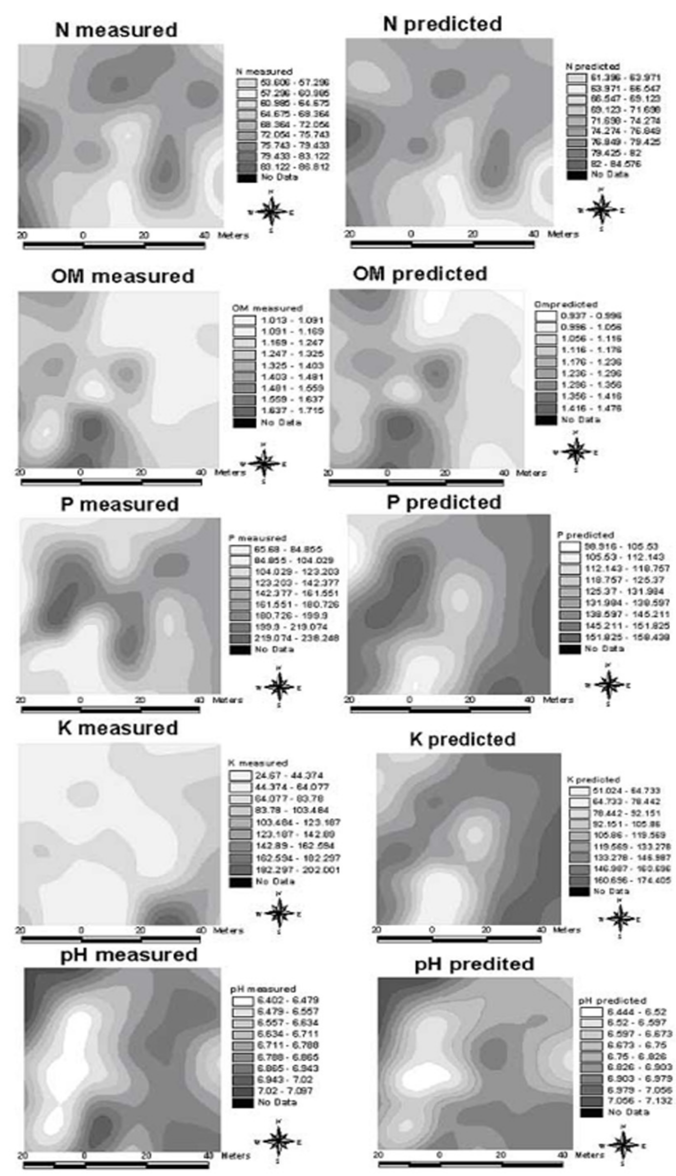


***Figure 4.** Spatial distribution maps of predicted and measured N, P, K, OM, and pH.*

The 165 samples were also divided into two sets for another purpose. Set I, with 135 samples, was used to develop a calibration model, with the equations developed using principal components analysis (PCA) and partial least squares (PLS). The best calibration was deemed to be the one with lowest root mean square error of prediction (RMSEP), the lowest standard error of prediction (SEP), the lowest standard deviation, and the highest coefficient of correlation (r). Each calibration equation developed from set I was then used to predict the constituent values for the independent spectra in set II. For each, the NIR-predicted values for set II were correlated with their measured values. Calibration statistics for each prediction model are shown in Table 1.

PCA reveals that the first principal component (PC1) accounts for the largest possible amount of variance in the data, while subsequent components account for successively less of the vari-

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ance, showing no particular trend with each constituent composition. Non-samples were removed from the prediction.

The prediction set demonstrated that NIR spectroscopy predicts N, OM, and pH, but not P and K in this soil. Statistics for predicted N, P, K, OM, and pH are shown in Figure 3.

Predicted and measured N, P, K, OM, and pH spatial distribution was interpolated by ArcView GIS 3.1 software using the spline method, which creates a smooth curve restrained by specified points. Spatial distribution maps are shown in Figure 4.

## Conclusion

NIR spectroscopy has the potential to accurately predict N, OM, and pH in this soil. Further investigation is required to try to make successful P and K predictions.

The slight variation between the maps obtained for measured and predicted N, OM, and pH, as well as the speed, easy operation, and portability of NIR instruments make NIR spectroscopy an appealing technology for precision-farming field monitoring.

## Author Information

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