NINETEEN-SOIL-PARAMETER CALIBRATION MODELS AND MAPPING FOR UPLAND FIELDS USING THE REAL-TIME SOIL SENSOR

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ABSTRACT

In precision agriculture, rapid, non-destructive, cost-effective and convenient soil analysis techniques are needed for soil management, crop quality control using fertilizer, manure and compost, and variable-rate input for soil variability in a field. The visible and near-infrared (Vis-NIR) spectroscopy is an effective measurement method for estimating several soil parameters at once.

We developed nineteen-soil-parameter (NSP) calibration models based on Vis-NIR (305–1700 nm) underground soil reflectance spectra collected using the Real-time soil sensor (RTSS) with a differential global positioning system, in order to create each parameter soil maps. NSP maps were drawn using ArcGIS software. The investigated NSP were moisture content, soil organic matter, pH, electrical conductivity, cation exchange capacity, total carbon, ammonium nitrogen, hot water exchangeable nitrogen, nitrate nitrogen, total nitrogen, exchangeable potassium, exchangeable calcium, exchangeable magnesium, hot water soluble soil boron, soluble copper, exchangeable manganese, soluble zinc, available phosphate and phosphate absorption coefficient. The experimental site is a commercial upland field with alluvial soil located in Hokkaido, Japan. To develop NSP calibration models, soil samples were collected from the corresponding scanning positions of Vis-NIR data. Partial least-squares regression coupled with leave-one-out cross-validation method were used to establish the relationship between Vis-NIR data and soil chemical analysis value, and the Unscrambler software was used. In the sensitivity analysis, accuracy of NSP calibration models were obtained for coefficient of determination (R²: from 0.64 to 0.86, as validation result).

Keywords: Real-time soil sensor, Vis-NIR spectroscopy, PLSR, soil maps

INTRODUCTION

In precision agriculture, rapid, non-destructive, cost-effective and convenient soil analysis techniques are needed for soil management decision, crop quality control using manure, fertilizer and compost, and variable-rate input for soil variability in an agricultural field. In particular, it is required that multiple soil parameters are estimated by one measurement data. The visible (Vis) and near infrared (NIR) spectroscopy is one of the promising techniques that measure rapidly multiple soil parameters. Many previous studies were based on measurements carried out in a laboratory environment, which soil samples were collected from agricultural fields. In our past many studies, the on-the-go type soil sensor collects Vis-NIR soil reflectance spectra data in agricultural fields, a lot of soil samples of the same location was analyzed chemically, and the calibration model was developed using multivariate statistics method. Calibration models of nineteen-soil-parameters were evaluated using the partial least square regression method. We obtained nineteen-soil maps as: moisture content (MC), soil organic matter (SOM), pH, electrical conductivity (EC), cation exchange capacity (CEC), total carbon (C-t), ammonium nitrogen (N-a), hot water exchangeable nitrogen (N-h), nitrate nitrogen (N-n), total nitrogen (N-t), exchangeable potassium (K₂O), exchangeable calcium (CaO), exchangeable magnesium (MgO), hot water soluble soil boron (B), soluble copper (Cu), exchangeable manganese (Mn), soluble zinc (Zn), available phosphate (P-a), and phosphate absorption coefficient (PAC). The aims of this study are as follows:

- 1) To develop NSP calibration models using PLSR on Vis-NIR spectra data collected by the Real-time soil sensor.
- 2) To draw NSP maps of the measured maps and the predicted maps.

MATERIALS AND METHODS

Experimental Site

Fig. 1 shows the experimental site (8.94 ha) in Hokkaido, Japan. The experiment was conducted on 2 fields (Field A: 303×146 m, Field B: 303×148.8 m) after crop harvesting for development of NSP calibration models in August, October 2008 and in November 2009. The soil is alluvial soil. The crop rotation system used at the site is five crops for five years: winter wheat – sugar beet – soy bean – potato – green manure.



Fig. 1. Location of the experimental site and the crop rotation system.

The Real-time Soil Sensor

An outline of the RTSS is shown in Fig. 2. The RTSS was designed to collect underground soil reflectance spectra at depths of 0.05 to 0.35 m at 0.05 m spacing. The penetrator tip with flat plane edge ensures uniform soil cuts, and the soil flattener behind finishes to produce a uniform surface. The sensor unit's housing included core devices of the system, such as a personal computer, a halogen lamp, two spectrophotometers (Vis and NIR range), differential global receiver. positioning system (DGPS) CCD camera and etc. The spectrophotometer for Vis had a 256-pixel linear photodiode array to quantify the reflected energy in the spectral range of 310 to 1,100 nm. A 128-pixel linear diode array (Multiplexed InGaAs) for NIR was used to quantify the reflected energy in the spectral range of 950 to 1.700 nm. As shown in Pic. 1, the touch monitor is able to display the soil surface images during the experiment from CCD camera, and recorded to the memory card too. The displayed images were used to watch for emergencies, such as blockage with obstacles, and the images gave information to eliminate data in data analysis, for example calibration outliers.



Fig. 2. A tractor-mounted the RTSS and sensor arrangement.



Pic.1 Images of uniform underground soil surface captured by CCD camera.

Data Collection and Soil Sampling

As shown in Fig. 3, the tramline matched the line (24 m spacing) of the crop protection sprayer. Small black dots indicate the collection position for underground soil reflectance spectra data. Large black dots indicate the collection position for soil samples corresponding to the position of underground soil reflectance spectra data. For calibration purposes, a total of 262 soil samples were collected from field A and B. These soil samples were analyzed at our laboratory and the Agricultural Product Chemical Research Laboratory (Hokkaido, Japan).



Fig. 3. Tramline used as a reference for RTSS travel and a data collecting point.

Data Analysis and Soil Mapping

To reduce noise and enhance weak signals, Vis-NIR data were subjected to Savitzky-Golay 2nd derivative pretreatment. The sensitivity analysis for NSP calibration models were developed using the PLSR technique in the Unscrambler v9.8 (CAMO ASA, Norway). A total of 262 data of pretreated with 2nd derivative were used as the calibration dataset for full-cross validation. As shown in Fig. 4, original soil absorbance data (a) were converted to (b).

NSP maps of the measured data and predicted data were drawn using Inverse Distance Weighted method (IDW) by ArcMap v9.2 (ESRI, USA).



Fig. 4. Original soil absorbance data (a), Soil absorbance data of pretreated with 2nd derivative (b).

RESULTS

Table 1 shows the results of sensitivity analysis on NSP models. These obtained results, outliers were removed until the correlation coefficient of 0.8 or more using residual sample variance information in the Unscrambler software.

As shown in Fig. 5, following measured and predicted soil maps for MC, SOM, pH, EC, CEC, C-t, CaO, K₂O, MgO, N-a, N-h, N-n, N-t, B, Cu, Mn, Zn, P-a and PAC were draw using the IDW method. Black (C-t: yellow) dots of " \cdot " in each maps are viewing the position of Vis-NIR data collecting or soil sampling.

NSP	Unit	Range	рт	PC	Ν	Calibration			Prediction		
		(nm)	11	PC		R _{cal}	R^2_{cal}	RMSE _{cal}	R_{val}	R^2_{val}	RMSE_{val}
MC	%	500 - 1600	$2^{nd} D$	6	262	0.94	0.88	2.08	0.93	0.86	2.22
SOM	%	500 - 1600	$2^{nd} D$	7	262	0.90	0.81	0.46	0.88	0.78	0.51
pН	pH unit	500 - 1600	$2^{nd} D$	8	224	0.86	0.74	0.21	0.80	0.65	0.25
EC	$mS cm^{-1}$	500 - 1600	$2^{nd} D$	6	209	0.84	0.71	0.01	0.80	0.64	0.01
CEC	me 100g ⁻¹	500 - 1600	$2^{nd} D$	7	262	0.89	0.79	1.68	0.87	0.75	1.84
C-t	%	500 - 1600	$2^{nd} D$	7	262	0.93	0.86	0.17	0.91	0.82	0.19
CaO	mg 100g ⁻¹	500 - 1600	$2^{nd}D$	7	213	0.85	0.73	21.87	0.80	0.64	25.21
K_2O	mg 100g ⁻¹	500 - 1600	$2^{nd} D$	7	183	0.85	0.72	1.92	0.80	0.65	2.15
MgO	mg 100g ⁻¹	500 - 1600	$2^{nd} D$	8	233	0.86	0.74	2.77	0.80	0.65	3.22
N-a	mg 100g ⁻¹	500 - 1600	$2^{nd}D$	7	229	0.85	0.72	0.10	0.80	0.64	0.12
N-h	mg 100g ⁻¹	500 - 1600	$2^{nd} D$	7	229	0.84	0.71	0.49	0.80	0.64	0.55
N-n	mg 100g ⁻¹	500 - 1600	$2^{nd} D$	6	189	0.84	0.70	0.11	0.80	0.64	0.12
N-t	%	500 - 1600	$2^{nd}D$	6	262	0.90	0.80	0.01	0.88	0.77	0.01
В	ppm	500 - 1600	$2^{nd}D$	6	238	0.84	0.70	0.13	0.80	0.65	0.14
Cu	ppm	500 - 1600	$2^{nd} D$	6	226	0.83	0.69	0.20	0.80	0.64	0.22
Mn	ppm	500 - 1600	$2^{nd} D$	9	189	0.87	0.76	2.04	0.80	0.64	2.51
Zn	ppm	500 - 1600	$2^{nd} D$	5	208	0.83	0.68	0.36	0.80	0.64	0.39
P-a	mg 100g ⁻¹	500 - 1600	$2^{\text{nd}} D$	6	258	0.85	0.72	8.19	0.81	0.65	9.15
PAC	Non	500 - 1600	$2^{nd} D$	7	262	0.92	0.84	63.48	0.90	0.81	69.50

Table 1. The result of sensitivity analysis on NSP models.

NSP: Nineteen-soil-parameter.

PT: Pretreatment.

PC: Principal component.

N: Number of samples.

 $R_{cal} \& R_{val}$: Correlation coefficient. $R^{2}_{cal} \& R^{2}_{val}$: Coefficient of determination.

RMSE_{cal} & RMSE_{val}: Root mean square error.









Measured Measured Predicted N-t В

1.24 - 1.31

1.16 - 1.23

1.08 - 1.15

1.00 - 1.07

0.50 - 0.99



PAC

Fig. 5. Measured and predicted soil maps comparison of NSP on field A in 2009.

CONCLUSIONS

We obtained NSR calibration models for upland field on alluvial soil. Accuracy of NSR calibration models were more than 0.64 (R^2_{val}).

NSR maps on distribution situation of the predicted soil maps were almost the same with the measured soil maps.

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