바이오시스템공학 (*J. of Biosystems Eng.*)
Vol. 36, No. 1, pp.33~39 (2011. 2)
DOI:10.5307/JBE.2011.36.1.33

Research Article

Open Access

광반사를 이용한 한국 논 토양 특성 추정

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Estimation of Korean Paddy Field Soil Properties Using Optical Reflectance

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Abstract

An optical sensing approach based on diffuse reflectance has shown potential for rapid and reliable on-site estimation of soil properties. Important sensing ranges and the resulting regression models useful for soil property estimation have been reported. In this study, a similar approach was applied to investigate the potential of reflectance sensing in estimating soil properties for Korean paddy fields. Soil cores up to a 65-cm depth were collected from 42 paddy fields representing 14 distinct soil series that account for 74% of the total Korean paddy field area. These were analyzed in the laboratory for several important physical and chemical properties. Using air-dried, sieved soil samples, reflectance data were obtained from 350 to 2500 nm on a 3 nm sampling interval with a laboratory spectrometer. Calibrations were developed using partial least squares (PLS) regression, and wavelength bands important for estimating the measured soil properties were identified. PLS regression provided good estimations of Mg (R^2 = 0.80), Ca (R^2 = 0.77), and total C (R^2 = 0.92); fair estimations of pH, EC, P_2O_5, K, Na, sand, silt, and clay (R^2 = 0.59 to 0.72); and poor estimation of total N. Many wavelengths selected for estimation of the soil properties were identical or similar for multiple soil properties. More important wavelengths were selected in the visible-short NIR range (350-1000 nm) and the long NIR range (1800-2500 nm) than in the intermediate NIR range (1000-1800 nm). These results will be useful for design and application of in-situ close range sensors for paddy field soil properties.

Keywords : Precision agriculture, Soil sensor, Soil property, Optical reflectance

1. INTRODUCTION

Precision agriculture is well established in North America, Europe, and Australia, where production fields are relatively large. Precision agriculture has also attracted interest and limited adoption in Asian countries including Korea, where fields are 0.3 to 1.0 ha in size. For successful implementation of precision agriculture, site-specific quantification of those soil physical and chemical properties that affect soil quality and crop production is important. Many of these properties may change on a finer spatial resolution than can be practically analyzed with laboratory methods due to time and cost of the sampling and analysis procedures. In addition, many soil properties vary considerably by depth, requiring sampling and analysis at multiple depths. Thus, it would be preferable to replace the standard laboratory methods with another approach that could allow accurate characterization of spatial and vertical variability at a reasonable cost, and with reliability and timeliness.

Optical diffuse reflectance spectroscopy (DRS) is a soil

This study was financially supported by research fund of Chungnam National University in 2008. The article was submitted for publication on 2011-02-01, reviewed on 2011-02-09, and approved for publication by editorial board of KSAM on 2011-02-15. The authors are Sun-Ok Chung, Assistant Professor, Dept. of Biosystems Machinery Engineering, Chungnam National University, Daejeon, Ki-Youl Jung, Agricultural Researcher, Dept. of Functional Crop, National Academy of Crop Science, Milyang, Republic of Korea, and Kenneth A. Sudduth, Agricultural Engineer, USDA-ARS Cropping Systems and Water Quality Research Unit, Columbia, Missouri, USA. Corresponding author: S. O. Chung, Dept. of Biosystems Machinery Engineering, Chungnam National University, 79 Daehangno, Yuseong-gu, Daejeon, 305-764, Republic of Korea; Fax: +82-42-823-6246; E-mail <sochung@cnu.ac.kr>.

sensing technology that has been investigated for over three decades. Diffuse reflectance spectroscopy is based on the interaction between incident light and soil surface properties, such that the characteristics of the reflected light vary due to the surface physical and chemical properties (Mouazen et al., 2005). Investigators have successfully estimated soil physical and chemical properties with visible (VIS; 400-700 nm), near-infrared (NIR; 700-2500 nm), and mid-infrared (MIR; 2500-25000 nm) DRS. Viscarra Rossel et al. (2006) reported that MIR spectra generally produced more accurate results, but the technology was more complex and expensive than that required for VIS-NIR measurement. Because of this trade-off between the relative accuracy of measurements and the cost of the instrumentation, a majority of DRS research has been carried out in the VIS, NIR, or VIS-NIR wavelength ranges.

A major focus of NIR and VIS-NIR spectroscopy has been estimation of soil carbon, either total C (Chang et al.,2001; Chang and Laird, 2002), or organic C (Sudduth and Hummel, 1991; Islam et al., 2003). Results have also been reported for cation exchange capacity (CEC), Ca, K, texture (sand, silt, and clay fractions), Mg, pH, total N, and other soil chemical properties (Sudduth and Hummel, 1993; Islam et al., 2003; Lee et al., 2003; Lee et al., 2009). Viscarra Rossel et al. (2006) and Stenberg et al. (2010) provide thorough reviews of soil DRS applications, including accuracy statistics.

The DRS sensing approach has also been applied to Asian fields. Shibusawa et al. (2005) developed a real-time multi-spectral soil sensor using nine wavelengths of light. Data collected at 552, 651, 739, 811, 926, 1007, and 1457 nm were used to estimate moisture content (MC) and data at 1303 and 1650 nm were used for soil organic matter (SOM) content. Using partial least squares (PLS) regression, MC was estimated with R^2 of 0.76 and standard error of calibration (SEC) of 2.50% for an Andisol, but SOM was not estimated successfully. Morimoto et al. (2004) used the same sensor body, but different sensing hardware. They collected absorbance spectra from 500 to 1650 nm with a 7 nm interval for 1300 soil samples from Japanese paddy and dry fields and used those spectra to estimate SOM, total N, pH, and MC. Using a neural network approach, MC, pH, SOM, and total N were estimated with R^2 values of 0.91, 0.75, 0.95, and 0.96, respectively.

Although sensing and analysis of the DRS signal over a wide spectral range can provide the information needed to quantify soil physical and chemical properties, another more efficient approach is to identify and use those wavelength ranges or specific wavelengths most strongly related to the properties of interest. This improvement in efficiency is particularly important when developing an instrument for the specific purpose of soil sensing, as a reduction in sensing range may allow a concomitant reduction in complexity and cost of the device. However, this approach is difficult because even for the same soil property, the best sensing range may change depending on the analysis method and dataset used. For example, Krishnan et al. (1980) reported better estimation of SOM (or organic C) with VIS data than with NIR data. However, Sudduth and Hummel (1991) found that NIR data gave the best estimates of organic C, obtaining best results (R^2 = 0.91) when using reflectance data from 12 NIR bands in the range from 1720 to 2380 nm. Similarly, Henderson et al. (1992) reported that for soils formed from different parent materials, five long NIR bands (1955-1965, 2215, 2265, 2285-2295 and 2315-2495 nm) gave the best estimation (R^2 > 0.92) of organic C.

Our overall goal in this project is to develop a VIS-NIR or NIR soil property sensor that can estimate multiple soil properties for Korean paddy fields. Specific objectives of the research reported here were to 1) assess the accuracy of DRS for estimating variation in several important soil properties across a wide range of soils from Korean paddy fields, and 2) determine the wavelength ranges and/or specific wavelengths important for estimation of these soil properties.

2. MATERIALS AND METHODS

A. Soil Sampling and Laboratory Analysis

Soils used in this study were obtained from 42 paddy fields representing 14 distinct soil series that account for 74% of the total Korean paddy field area. Descriptive characteristics of these soils, which exhibited differences in parent material, topography, and texture, were given by Lee et al. (2008). Five 9-cm diameter, 65-cm long sample cores were obtained from each field, segmented by depth on a 5-cm interval, mixed for each depth, and the total 631 samples were analyzed at the Yeongnam Agricultural Research Institute using methods described by the National Institute of Agricultural Science and Technology (2000). Summary

Table 1 Summary statistics of laboratory-determined soil properties(Lee et al., 2008)

Soil property	Minimum	Maximum	Mean	Standard deviation	Skewness
pH	4.30	8.16	6.23	0.71	-0.17
EC (dS m^{-1})	0.00	2.96	0.41	0.41	2.65
P_2O_5 (mg kg^{-1})	0.01	584.32	68.62	104.34	2.87
K (cmol kg^{-1})	0.03	0.82	0.17	0.14	2.48
Ca (cmol kg^{-1})	1.19	22.62	5.52	3.22	1.72
Mg (cmol kg^{-1})	0.30	5.97	1.53	1.14	1.60
Na (cmol kg^{-1})	0.04	1.85	0.25	0.25	3.44
Total C (%)	0.12	3.18	0.96	0.68	1.11
Total N (%)	0.00	2.68	0.19	0.29	4.23
Sand (%)	0.12	96.58	43.84	23.45	-0.17
Silt (%)	1.56	80.05	38.82	17.02	0.33
Clay (%)	1.86	45.67	17.33	9.32	0.82

statistics of laboratory measurements are given in Table 1. There were wide variations in most of the soil properties since the samples were from different soil series and depths.

B. Spectral Data Acquisition

Soil spectral reflectance data were obtained in the laboratory using an ASD FieldSpec 3[1)] spectrometer (Analytical Spectral Devices, Boulder, Colo.). The spectrometer used three detector systems: 1) a silicon photodiode array for 350-1000 nm, 2) an InGaAs detector for 1000-1800 nm, and 3) an enhanced InGaAs detector for 1800-2500 nm. Spectra recorded between 350 and 2500 nm were output on a 3-nm interval (Fig. 1). Reflectance data were preprocessed to remove high-noise measurement bands and improve stability of the regression. The first 30 readings at the lower visible wavelengths were deleted due to their low signal-to-noise ratio, as suggested by Lee et al. (2009); thus the reduced dataset covered 440-2500 nm. Then, data were transformed from reflectance to absorbance (log10 [1/reflectance]) and normalized by mean-centering. Detailed information on soil sampling, analysis, and spectral data acquisition was reported by Lee et al. (2008).

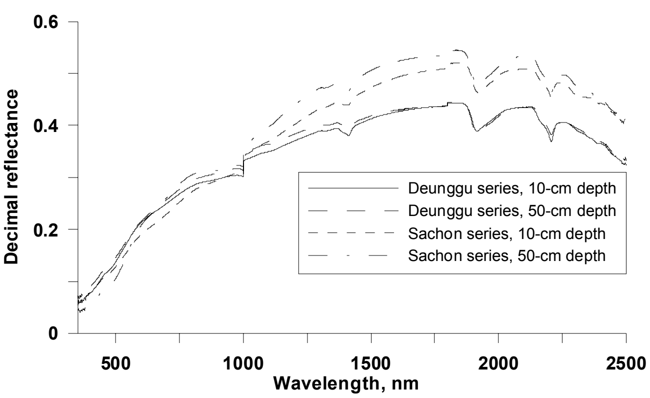

Fig. 1 Example soil reflectance spectra for two soil series at two depths.

1) Mention of trade names or commercial products is solely for the purpose of providing specific information and does not imply recommendation or endorsement by the Chungnam National University, Republic of Korea, the US Department of Agriculture or their cooperators.

C. Analytical Procedures

Partial least squares (PLS) regression implemented in Unscrambler version 9.1 (CAMO Inc., Oslo, Norway) was used to develop calibrations between soil properties and reflectance spectra. A key step in PLS regression is selecting the optimal number of factors to best represent the calibration data without overfitting. To do this, we applied a 10-fold cross-validation procedure within the Unscrambler software. This procedure calculated the validation dataset variance, coefficient of determination (R^2), and root mean square error of prediction (RMSEP) for models containing from 1 to 20 factors and determined a recommended number of factors to minimize estimation error. The calibration model was then obtained from the full dataset using this number of factors.

Model evaluation was based on R^2, RMSEP, and RPD (Ratio Performance Deviation), the ratio of standard deviation to RMSEP. RPD is a useful measure of fit when comparing results from datasets containing different degrees of variability, with a higher RPD indicating a more accurate estimation

(Williams, 1987; Hummel et al., 2001). We used the following categories: poor estimation when $R^2 \leq 0.65$ or RPD $\leq$ 1.5, fair estimation with $0.65 < R^2 < 0.80$ or 1.5< RPD < 2.0, and good estimation when $R^2 \geq 0.80$ or RPD ≥ 2.0, as defined by Lee et al. (2008 and 2009).

Those wavelengths most significant for estimating soil properties were identified using the B-matrix computed by the Unscrambler software. The B-matrix contains coefficients relating the original independent variables (reflectance values in this case) to the dependent (soil property) variable, and independent variables with larger B-coefficients can be viewed as contributing more to the overall regression model.

3. RESULTS AND DISCUSSION

A. Soil Property Estimation using PLS

Table 2 shows the cross-validated PLS statistics for estimation of the soil properties. Good estimates were obtained for Mg and total C, based on both R^2 and RPD criteria, and Ca, based on the RPD criterion. Fair estimates were obtained for pH, EC, K, Na, and sand fraction, based on both criteria; for Ca based on the R^2 criterion; and for silt and clay fractions based on the RPD criterion. Poor estimates were obtained for total N, based on both criteria, and P_2O_5, silt and clay fractions, based on the R^2 criterion.

Table 2 PLS cross-validation statistics for soil property estimation (Bold entries indicate good estimates and italic entries indicate fair estimates according to R^2 and RPD criteria)

Soil Property	Validation R^2	RPD	No. of factors
pH	*0.70*	*1.82*	16
EC (dS m^{-1})	*0.72*	*1.86*	15
P_2O_5 (mg kg^{-1})	0.59	*1.56*	14
K (cmol kg^{-1})	*0.72*	*1.75*	18
Ca (cmol kg^{-1})	*0.77*	2.08	14
Mg (cmol kg^{-1})	0.80	2.24	18
Na (cmol kg^{-1})	*0.72*	*1.92*	20
Total C (%)	0.92	3.58	14
Total N (%)	0.01	1.04	1
Sand (%)	*0.72*	*1.89*	11
Silt (%)	0.64	*1.67*	10
Clay (%)	0.62	*1.67*	13

Figure 2 shows scatter plots of estimated vs. measured values of four selected soil properties which exhibited good or fair results: Ca (top left), Mg (top right), total C (bottom left), and sand fraction (bottom right). For Ca, Mg, and total C, better estimates were observed at medium values than at lower and higher values where underestimations were obtained. At very low measured values, some negative estimates were seen. Estimated values were fairly well distributed around the 1:1 line for sand fractions, but negative estimates were also observed for very low measured values.

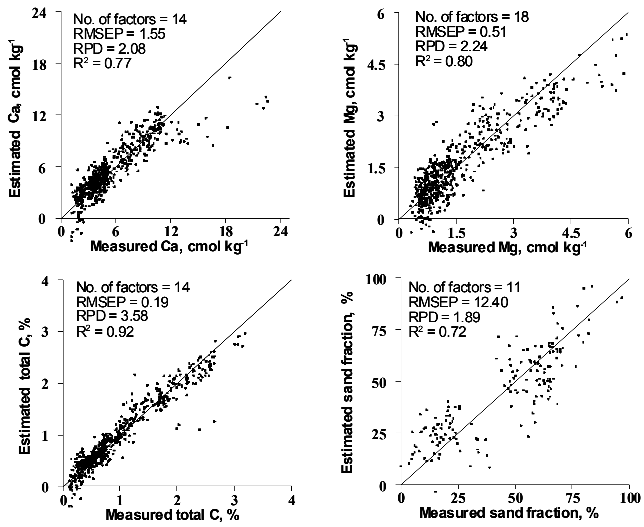

Fig. 2 Scatter plots of estimated vs. measured values of Ca (top left), Mg (top right), total C (bottom left), and sand fraction (bottom right). For reference, 1:1 lines are also shown.

B. Identification of Important Wavelengths

Figure 3 shows B-matrix coefficients from the PLS analysis. Patterns of the B-matrix plots were different for different soil properties, but some similarities were present for multiple properties. For example, many of the B-matrix local peaks and valleys were observed around the local peaks and valleys of raw reflectance spectra (see fig. 1). Patterns of the B-matrix plots were very similar between EC and K, between pH and Ca, and between Mg and Na. Patterns for P_2O_5 and total C were similar to those for pH and Ca, through the wavelengths of detector 2 (<1800 nm), but opposite at the wavelengths of detector 3 (1800 to 2500 nm). Patterns for sand and silt were opposite for the entire wavelength range. These indicated that some wavelengths or wavelength ranges would be common for estimation of multiple soil properties.

Relatively large local peaks and valleys were identified and corresponding wavelengths were summarized in table 3.

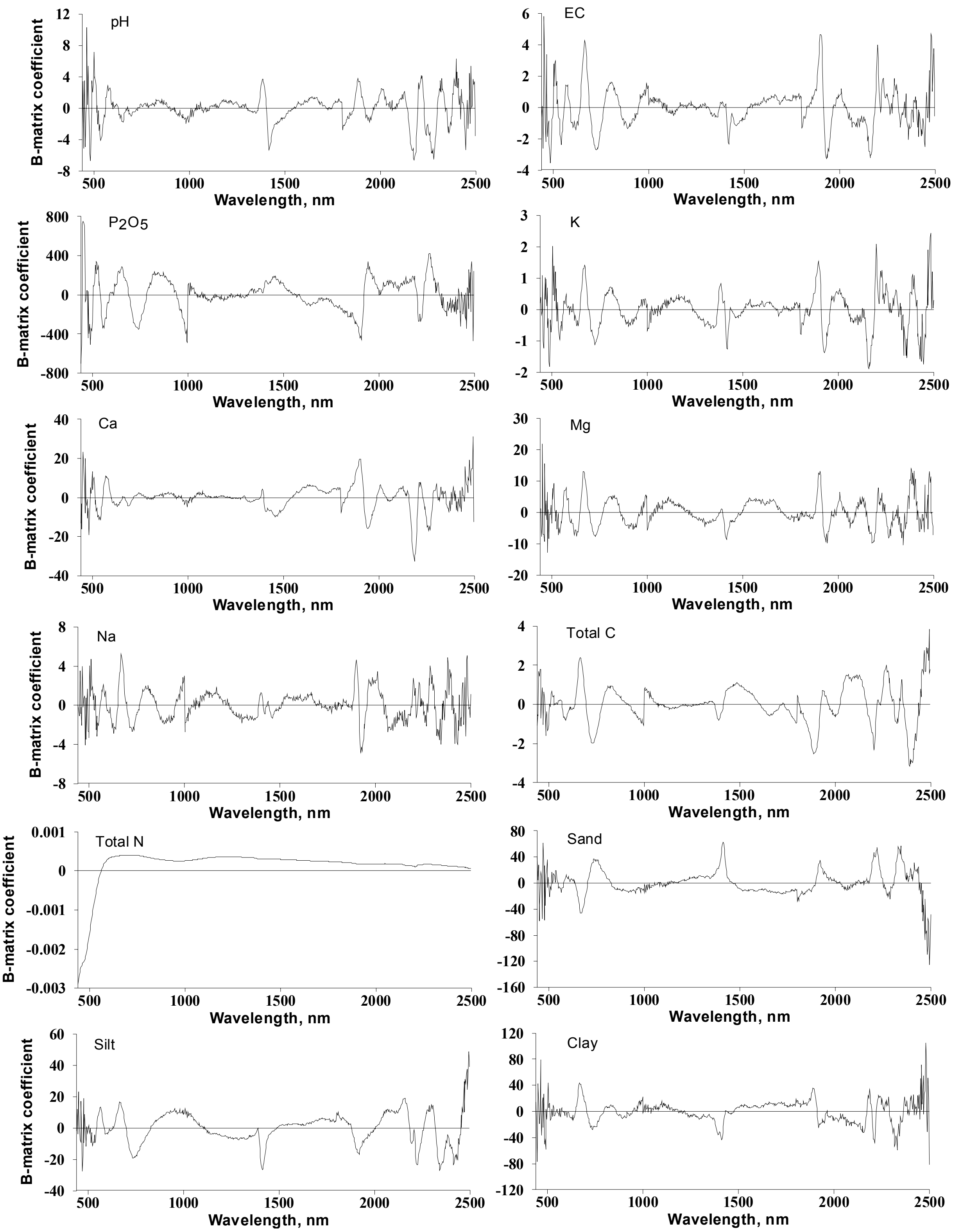

Fig. 3 PLS B-matrix coefficient plots.

Determining local peaks at very low and very high wavelengths was difficult since high frequency fluctuations were present, and peaks were present in most cases around the transition wavelengths between the detectors (i.e., 1000 and 1800 nm); therefore we disregarded peaks within 50 nm of 440, 1000, 1800, and 2500 nm. As expected, many wavelengths

Table 3 Wavelengths selected at local peaks of B-matrix coefficient plots from PLS analyses.

Soil Property	Wavelengths selected, nm		
	Detector 1 (440 - 1000 nm)	Detector 2 (1000 - 1800 nm)	Detector 3 (1800 - 2500 nm)
pH	500, 536, 572	1382, 1415	1883, 2006, 2126, 2177, 2219, 2279, 2321, 2360, 2396, 2447
EC	512, 542, 575, 620, 665, 725, 806, 890	1418	1898, 1931, 2009, 2159, 2198, 2447
P_2O_5	521, 560, 653, 740, 824	1451	1907, 1943, 2186, 2219, 2264
K	503, 542, 671, 725, 809	1166, 1385, 1418	1895, 1928, 2009, 2159, 2198, 2360, 2390, 2447
Ca	500, 542, 569	1391, 1460, 1637	1901, 1943, 2009, 2126, 2186, 2213, 2261, 2303, 2366
Mg	512, 536, 575, 629, 668, 728, 821, 923	1112, 1391, 1415, 1535	1904, 1943, 2009, 2126, 2177, 2210, 2264, 2342, 2381
Na	509, 542, 575, 629, 668, 728, 809, 905	1166, 1400	1898, 1922, 2009, 2063, 2198, 2264, 2285, 2342, 2378, 2429
Total C	590, 668, 734, 833	1391, 1487	1889, 1934, 2069, 2204, 2270, 2321, 2348, 2390
Total N	------------ No wavelengths identified --------------		
Sand	563, 590, 671, 737	1415	1919, 2219, 2285, 2342, 2414
Clay	503, 668, 737	1412	1889, 2186, 2213, 2234, 2330

were selected for multiple soil properties. For example, many wavelengths selected for sand and silt were identical (1919, 2342, and 2414 nm) or very similar (671 vs. 665, 737 vs. 734, and 2219 vs. 2222). Nine wavelengths selected for Ca (542, 569, 1391, 1901, 1943, 2009, 2126, 2213, and 2261 nm) were identical or similar to those for Mg. More important wavelengths were selected in the visible-short NIR range (440-1000 nm; detector 1) and the long NIR range (1800-2500 nm; detector 3) than in the intermediate NIR range (1000-1800 nm; detector 2). Wavelengths between 1412 and 1418, however, were selected as important for 7 soil properties.

Results described above showed that many of the Korean paddy field soil properties could be estimated with “good” or “fair” results using optical reflectance data, and multiple soil properties could be estimated using combinations of identical or similar wavelengths. It would be interesting to investigate potential of the optical sensing approach to soil samples from other cropping systems such as dry upland fields, greenhouses, and orchards. For practical implementation of an optical sensor, further investigation would be needed in the areas of wavelength selection, sensor design and fabrication, and evaluation of the sensor in various field conditions.

4. CONCLUSIONS

In this study, we investigated the potential of a VIS-NIR or NIR soil property sensor for estimating variation in several important soil properties across a wide range of soils from Korean paddy fields, and for determining the wavelength ranges and/or specific wavelengths important for estimation of these soil properties. We used soil samples from 14 distinct soil series accounting for 74% of the total Korean paddy field area, and soil spectral reflectance data from 440 to 2500 nm. Major findings were:

- PLS statistics showed that “good” estimations ($0.8 \leq R^2$, $2 \leq$ RPD) could be obtained for Mg, Ca, and total C. Fair estimations ($0.65 < R^2 < 0.8$, $1.5 <$ RPD < 2) were obtained for pH, EC, P_2O_5, K, Na, sand, silt, and clay. A poor estimation was obtained for total N.
- Plots of B-matrix coefficients from the PLS analysis showed similarities for multiple properties (e.g., EC and K, pH and Ca, Mg and Na), indicating some common wavelengths could be important for estimation of multiple soil properties.
- Important wavelengths selected from relatively large local peaks of the B-matrix plots included many wavelengths that were identical (e.g., 1919, 2342, and 2414

nm) or similar for multiple soil properties (e.g., sand and silt). More local peaks were present in the visible-short NIR range (440-1000 nm; detector 1) and the long NIR range (1800-2500 nm; detector 3) than in the intermediate NIR range (1000-1800 nm; detector 2). Wavelengths between 1412 and 1418, however, were selected for 7 of the soil properties.

These findings would be useful for development and application of a DRS sensor, but further research, such as application of the approach for soil samples from other cropping systems (e.g., greenhouse production), objective procedures for wavelength selection, and evaluation in field conditions, would be necessary steps toward successful implementation of the sensor.

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