RESEARCH ARTICLE OPEN ACCESS

Mapping the Soil Property based on Proximal Soil Sensing Approach to Study the Spatial and Temporal Variability

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Abstract:

Farmers should aware of with-in field variability of soil property in precision farming practice. The problem is how to provide reliable, fast and inexpensive information of soil property in the subsurface from numerous soil samples and repeated measurement. The proximal soil sensing has emerged as a rapid and low-cost method for extensive investigation of soil property. The objective of this research was to develop calibration models based on laboratory Vis-NIR spectroscopy to predict the value of soil property at different growth stages of soybean crop on two small farms (Gunung Kidul and Bantul) in Yogyakarta Province. Some standard methods of soil analysis were applied to measure the soil texture, soil moisture content, soil organic matters, pH, N, P, K, Fe, and cation exchange capacity of 80 soil samples. An ASD Field-spectrophotometer was used to measure the reflectance of 240 soil samples. The partial least square regression (PLSR) was performed to establish the relationship between the measured soil properties with Vis-NIR soil reflectance spectra. The criteria to select the best calibration model was the largest coefficient of multiple determinations (R^2) and the smallest of root mean square error (RMSE). The selected calibration model was used to predict soil property of other 160 samples. The ability of Vis-NIR spectra to predict values of soil property was categorized based on residual prediction deviation (RPD) values. The results revealed by RPD values showed that the models performed vary from *excellent* to *unreliable* to predict the value of soil property. Different pretreatment process following trial and error procedure should be performed in order to find the best correlations between the measured soil property and the spectra.The temporal and spatial soil variability maps of predicted soil property values were performed using the ArcGIS v.10.0 with inverse distance weighted (IDW) interpolation method. The map interpretation of soil variability with-in field was very helpful to study the correlation among the soil property and support the decision for farm management.

Keywords **—Soil property,proximal soil sensing, Vis-NIR spectroscopy, inverse distance weighted (IDW).**

I. INTRODUCTION

No two soils are exactly alike and variations occur over short distances, vertically and horizontally. There is a need for regular monitoring to detect changes in its status so as to implement appropriate management. Soil surveying may be performed at national levels for the inventory of soil resources, or for agriculture at regional, farm or field scales [1]. Due to the high number of soil variability, the information about the soil fertility is important for better land management. Variability of soil physical properties caused by natural processes can be regionalized with the assumption that the adjacent site tends to be similar or has slightly different value, which is then delineated into a polygon [2]. However, the degree of similarity highly depends on the scale of observation, such as a country, km, or just a few mm only.

In precision farming, soil maps are required on different scales to meet the requirements of planning at various levels. The larger the scale used, the more information will be available and vice-versa. Therefore, selecting the method for soil sampling is important in order to obtain an efficient sampling and adequate data for analysis.

Kodaira and Shibusawa [3] had generated high-resolution maps of soil properties variability using Vis-NIR spectroscopy Real-time Soil Sensor (RTSS) for prediction of 12 soil properties with the sample density of 24m x 24m in 4.43 ha and 4.51 ha fields of different time and crops within 3 years. Aliah et al. [4] with the same method using Vis-NIR spectroscopy RTSS mapped the moisture content, organic matter, total carbon, total nitrogen, and available phosphorus on 1,200 m^2 wetland rice in Japan. They measured the soil properties of three different soil depths with a sample density of 11 m x 5 m.

The quantitative spectral analysis of soil, using Vis and NIR reflectance spectroscopy requires sophisticated statistical techniques to discern the response of soil attributes from spectral characteristics. Various methods have been used to relate soil spectra to soil attribute [5]. The multivariate analysis is used because in fact the problem that occurs cannot be solved by simply link the two variables or see the effect of one variable to another. The selection of the best model in this analysis is important since not all predictor variables are significantly affected by the models. It depends on the number of the predictor variables involved in the model [6].

The most common calibration methods applied are based on linear regressions, namely stepwise multiple linear regression (SMLR), principal component regression (PCR), and partial least squares regression (PLSR). However, PLSR is often preferred by analysts because it relates the response and predictor variables so that the model explains more of the variance in the response with fewer components, it is more interpretable and the algorithm is computationally faster [1].

To evaluate the suitability of the model, Brodsky et al. [7]used several indicators. First, the coefficient of determination between the predicted and the observed value are performed general size of variance reduction. Second, the RMSE (root mean square error) is used to evaluate the prediction error in the model for each soil attribute. Cross-validation is used to determine the number of factors retained in the calibration model. The model with the lowest RMSE is the selected model.

The objective of this research was to develop calibration models based on laboratory Vis-NIR spectroscopy to predict the value of soil property at different growth stages of soybean crop on two small farms (Gunung Kidul and Bantul) in Yogyakarta Province. The observed soil propertieswere the soil texture, soil moisture content (SMC), soil organic matters (SOM), pH, N, P, K, Fe, cation exchange capacity (CEC) and the soil reflectance.

The PLSR with full cross-validation was performed to establish the relationship between the soil propertieswith the pre-treated Vis-NIR soil reflectance spectra. The selected calibration model was used to predict the other new samples of soil properties. The temporal and spatial variability of soil propertieswere performed in digital maps using inverse distance weighted (IDW) interpolation method. These maps gave much information to be interpreted carefully due to many factors affect the soil property. They could be used to support the process of decision making in field management.

II. METHODOLOGY

A. Location

The research was conducted at soybean farms in two locations, i.e. Blembeman, Natah Village, Nglipar District, Gunung Kidul Regency (7°51'39.0"S, 110°39'19.4"E) and Dodogan, Jatimulyo Village, Dlingo District, Bantul Regency (7°55'22.5"S, 110°29'08.7"E). Figure 1 shows the location of the research. The elevation of Nglipar ranges from 200 to 210 m asl., while Dlingo elevation ranges from 190 to 200 m asl. The slope variesbetween 5° to 10° which Dlingo was steeper than Nglipar.

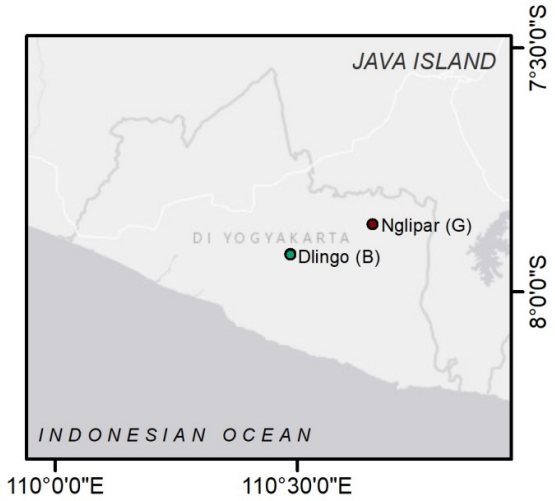

Fig.1Location of the research area:
G-field:Nglipar, GunungKidul Regency; B-field:Dlingo, Bantul Regency
(Background map source: ESRI et al., 2016) (Append.1)

B. Materials and Instruments

The soil was the main material to be observed in this research. The instruments used were:

1) Soil sampling tools (auger, trowel, bucket, sticks, zip lock plastic bag, marker, etc.).
2) GPS Garmin 60 csx.
3) Ring samples (Eijkelkamp) with 5 cm height and 5 cm in diameter.
4) The Analytical Spectral Devices FieldSpec® 3 (ASD Inc., Boulder, Colorado, USA), a portable spectroradiometer with a spectral range from 350 nm to 2500 nm.
5) Spectralon® Diffuse Reflectance Standard, a white reference panel for reflectance calibration.
6) Black aluminum ring plate to hold up the ASD probe vertically (modified by TUAT Laboratory),
7) A set of tools for soil properties analysis in soil Lab.

C. Soil Sampling

Due to the irregular and terrace shapes of the fields, the layout of sample points was set up using the grid method combined with a transect line of the 5-meter interval (Fig. 2). There were 30 sample points for each field marked with bamboo sticks. The soil was sampled 4 times according to the growth stages within one cropping season of soybean from October 2016 to January 2017, i.e. before planting, vegetative stage, generative stage and after harvesting. Each point was taken using auger at a depth of 5-15 cm about 500 grams and stored in a labeled zip lock plastic bag. The total samples from 2 locations and 4 stages sampling were 80 samples for soil properties analysis and 240 samples for spectroscopic measurements. All samples were air-dried, then gently crushed to break up larger aggregates, afterward removed the visible roots and each sample was sieved at 2 mm strainer.

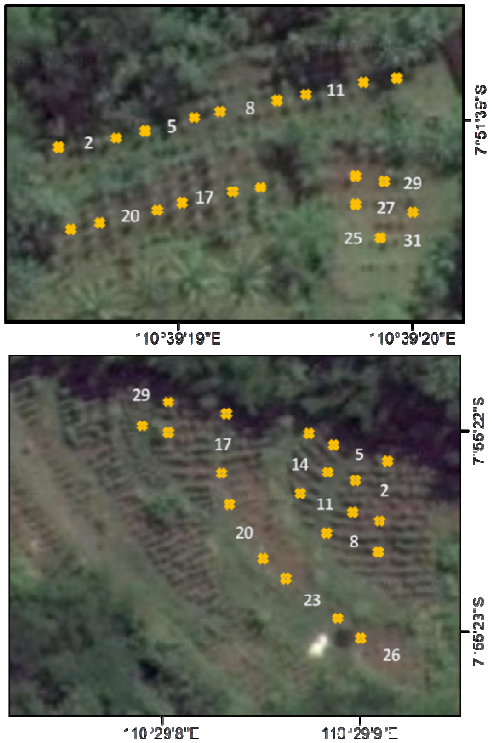

Fig. 2 Field layout
above: Nglipar field (1,500 m2), below: Dlingo field (1,300 m2)
(Modified from Google Earth 2012)

D. Soil Property Analysis

The soil properties were analyzed by the Soil Analytical Services Laboratory at UPN "Veteran" Yogyakarta (Table I).

E. Soil Spectral Analysis

The spectroscopy measurement was performed at the Agricultural Laboratory, University of Palangka Raya, Central Kalimantan, using ASD Field-spec® 3 350-2500 nm spectroradiometer. Each soil sample was placed into a 5 cm dia. ring sample (Eijkelkamp), and flattened the surface. A black aluminum ring plate (modified by TUAT

Laboratory, Japan) was fitted on the top of ring sample in order to hold the ASD probe of the optic sensors and keep the same distance from the probe tip to the sample surface (Fig. 3).

TABLE I.
THE SOIL PROPERTIES ANALYSIS METHOD AND NUMBER OF SAMPLES

Stage	B	V	G	A	Analysis Method
Para-meter	Number of samples				
MC	2x10	2x10	2x10	2x10	Gravimetric
SOM	2x10	2x10	2x10	2x10	Walkley and Black
pH	2x10	2x10	2x10	2x10	pH-H_2O
Total N	2x10	2x10	2x10	2x10	Kjeldahl
Pot. P	2x10	2x10	2x10	2x10	HCl 25% extract
Pot. K	2x10	2x10	2x10	2x10	HCl 25% extract
CEC	2x10	x	x	2x10	NH4OAc saturation pH 7
Fe	2x10	x	x	2x10	NH4OAc extract pH 4.8
Texture	2x10	x	x	2x10	Pipette method
Reflect-ance	2x30	2x30	2x30	2x30	Vis-NIR optical sensors

Note: MC (moisture content); SOM (soil organic matter); CEC (Cation exchange capacity); B (before planting); V (vegetative stage); G (generative stage); A (after harvesting)

Fig. 3. Soil reflectance measurement.
left: soils in ring sample; right: The ASD probe was inserted into a black aluminum ring plate at the sample surface

F. Multivariate Statistical Analysis

The data on soil properties were compiled in the Unscrambler X software to perform the multivariate analysis. The measured reflectance (R) spectra were transformed in absorbance through the log (1/R) to reduce noise, offset effects, and to enhance the linearity between the measured absorbance and soil properties [8]. To enhance weak signals and remove noise due to diffuse reflection, the absorbance spectra were pre-treated using the second derivative Savitzky and Golay method. Moreover, both edges of the spectra were removed as these parts of the spectra were unstable and rich in noise [4].

The calibration models were subsequently developed by applying the partial least-square regression (PLSR) technique coupled with full cross-validation to establish the relationship between the referenced value of soil properties with the pre-treated Vis-NIR soil absorbance spectra from the corresponding locations [4].

The selection criteria of any pre-treatment were the largest coefficient of multiple determinations (R2) and the smallest of Root Mean Square Error (RMSE). The full cross-validation ability of PLSR was given by the value of residual prediction deviation (RPD). The ability of Vis-NIR to predict values of soil properties can be grouped into three categories based on RPD values: category A or excellent (RPD >2.0) includes soil properties with measured vs. predicted R2 values between 0.80 and 1.00; category B or good (RPD = 1.4~2.0) and R^2 values between 0.50 and 0.80, and category C or unreliable (RPD <1.4;) and R2 < 0.50 [9]. RPD was given by the ratio of the standard deviation (SD) of the reference dataset to the root mean square error of full cross-validation ($RMSE_{val}$), as in Equation (1):

$$RPD = SD.\ RMSE_{val}^{-1} \qquad (1)$$

The selected calibration model was used to predict the soil properties of new samples.

III. RESULT AND DISCUSSION

G. Soil Properties of Referenced Samples

According to BBSDLP [10], the soils in the study area were tentatively classified as *Hapludults*and*Dystrudepts*at Nglipar, while soils at Dlingo were classified as *Hapludalfs, Eutrudepts,*and*Udorthents*. All of 80 reference samples from Nglipar and Dlingo were classified as clay with very low organic matter content (< 2%), and neutral pH.The statistics descriptions of each soil property samples are listed in Table II and III.

TABLE II.

STATISTICS DESCRIPTION OF NGLIPAR, GUNUNG KIDUL SOIL PROPERTIES

Location	GUNUNG KIDUL										
Parameter	MC	SOM	pH	N	P	K	Sand	Silt	Clay	Fe	CEC
Ref Samples	40	40	40	40	40	40	20	20	20	20	20
Mean	14,2799	0,9774	7,2213	0,1346	0,0053	0,0989	22,0356	13,6328	64,3316	3,8481	16,9164
Max	16,7976	1,3587	7,6600	0,2697	0,0094	0,2659	31,2846	23,6724	73,0389	5,8248	22,1638
Min	8,2472	0,5454	6,8100	0,0529	0,0024	0,0575	11,9237	5,5216	53,4934	1,9482	8,3742
Range	8,5505	0,8134	0,8500	0,2168	0,0069	0,2084	19,3609	18,1508	19,5455	3,8766	13,7896
Std Deviation	1,5190	0,1809	0,2061	0,0498	0,0019	0,0496	4,7215	4,6008	6,0155	1,2231	3,1421
Variance	2,3073	0,0327	0,0425	0,0025	0,0000	0,0025	22,2928	21,1676	36,1862	1,4959	9,8727
RMS	14,3585	0,9936	7,2241	0,1433	0,0056	0,1104	22,5110	14,3514	64,5982	4,0285	17,1914
Skewness	-1,8413	-0,2699	-0,3606	0,9524	0,3683	1,7757	0,0301	0,5052	-0,5853	-0,1070	-1,1029
Kurtosis	5,6866	-0,2004	-0,6450	1,0965	-0,7561	2,6733	0,0491	-0,0098	-0,8685	-1,4355	2,1584
Median	14,4953	0,9720	7,2900	0,1079	0,0051	0,0783	21,5714	12,9967	66,6618	4,0386	17,2682

TABLE III.
STATISTICS DESCRIPTION OF DLINGO, BANTUL SOIL PROPERTIES

Location	BANTUL										
Parameter	MC	SOM	pH	N	P	K	Sand	Silt	Clay	Fe	CEC
Ref Samples	40	40	40	40	40	40	20	20	20	20	20
Mean	15,0322	1,0961	7,0865	0,1451	0,0057	0,1077	22,6685	8,2367	69,0948	4,4080	20,0654
Max	19,3402	1,9697	7,4500	0,4926	0,0110	0,2205	35,3679	16,2519	74,7247	6,3197	25,7213
Min	12,6050	0,7737	6,3200	0,0527	0,0019	0,0569	16,5940	0,9277	63,5573	1,9511	14,4988
Range	6,7352	1,1960	1,1300	0,4399	0,0091	0,1637	18,7739	15,3242	11,1674	4,3686	11,2226
Std Deviation	1,3685	0,2427	0,2271	0,1120	0,0019	0,0507	4,3982	3,5632	3,5734	1,1787	3,4465
Variance	1,8729	0,0589	0,0516	0,0125	0,0000	0,0026	19,3444	12,6962	12,7691	1,3894	11,8784
RMS	15,0928	1,1220	7,0900	0,1824	0,0060	0,1188	23,0702	8,9389	69,1826	4,5552	20,3446
Skewness	0,7647	2,0011	-0,8955	2,3940	0,8048	1,1555	1,1949	0,3175	-0,0648	-0,4031	-0,0312
Kurtosis	1,3130	5,3955	1,9673	5,0189	0,9027	-0,3216	2,4084	0,2943	-1,1782	-0,2052	-1,2194
Median	14,9028	1,0561	7,1000	0,1076	0,0051	0,0838	21,9316	7,6560	69,3783	4,3632	20,1053

H. Soil Reflectance of Referenced Samples

Soil reflectance can be influenced by a number of factors, such assoil texture, surface roughness, organic matter content, color andmoisture content [11].Field soil reflectance is reduced, particularly in the visible portion of the spectrum, when the moisture content is high [12]. Soil moisture and organic matter increase soil absorbency and result in overall lower soil reflectance[13].Figures4 and 5 describe the soils reflectance of Nglipar and Dlingoat four stages of soybean growth.

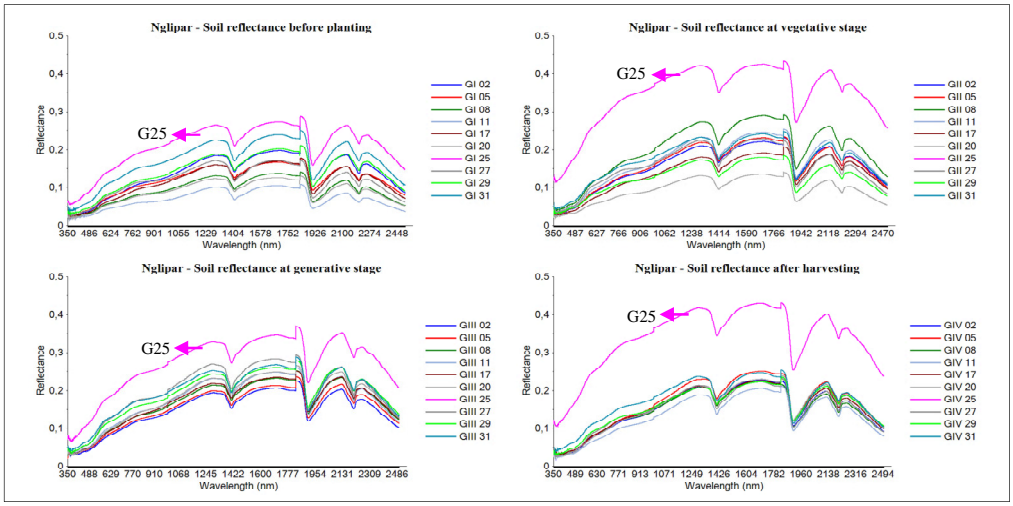

Fig.4 The spectral graphs of Gunung Kidul soil reflectance from 350-2500 nm

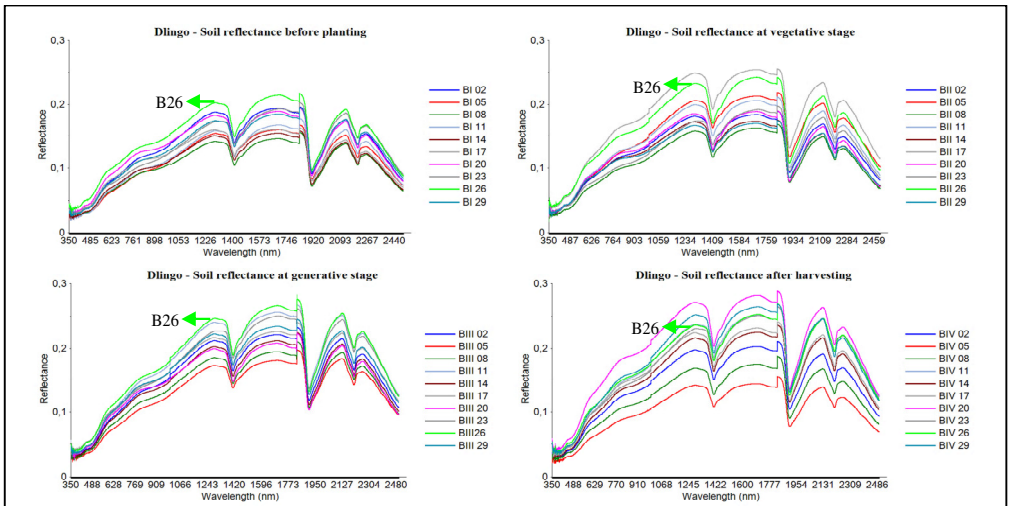

Fig.5 The spectral graphs of Dlingo soil reflectance from 350-2500 nm

I. The calibrationand prediction models

The summary of selected calibration models for each soil property using PLSR method and the RPD category are shown in Table IV and V. The selected calibration models in this research were using same pretreatments for all soil properties. The prediction values of soil properties were then applied to generate the variability map of soil properties.

TABLE IV.
THE SUMMARY OF PLSR AND RPD RESULTS OF GUNUNG KIDUL SOIL PROPERTIES

Soil Property	Sample for Calib	Outliers	PC number	CALIBRATION R^2_{cal}	CALIBRATION $RMSE_{cal}$	PREDICTION R^2_{val}	PREDICTION $RMSE_{Val}$	SD	RPD SD/RMSEV	RPD category
MC	40	7,11,19,26,28,34	3	0,7566	0,5050	0,6131	0,6560	1,5190	2,3155	A
SOM	40	6,11,12,21,31,38	6	0,9555	0,0372	0,5815	0,1176	0,1809	1,5379	B
pH	40	5,10,19,25,30,34	7	0,9787	0,0299	0,6098	0,1319	0,2061	1,5623	B
Ntot	40	12,21,23,27,30,33	1	0,1432	0,0433	0,0454	0,0471	0,0498	1,0574	C
P	40	12,16,27,29,34,40	7	0,9912	0,0002	0,4435	0,0014	0,0019	1,3744	C
K	40	9,10,15,29,33,36	6	0,9709	0,0082	0,7903	0,0228	0,0496	2,1742	A
Fe	20	5,9,14,15	6	0,9986	0,0417	0,7282	0,6251	1,1787	1,8857	B
CEC	20	11,12,14,15	2	0,7537	1,3109	0,4900	2,0119	3,1421	1,5618	B
Texture										
SAND	20	1,5,7,14	6	0,9985	0,1855	0,6686	2,9532	4,7215	1,5988	B
SILT	20	5,9,11,16	6	0,9986	0,1579	0,7881	2,0713	4,6008	2,2212	A
CLAY	20	1,4,8,15	6	0,9986	0,2349	0,8261	2,7754	6,0155	2,1674	A

TABLE V.
THE SUMMARY OF PLSR AND RPD RESULTS OF BANTUL SOIL PROPERTIES

Soil Property	Sample for Calib	Outliers	PC number	CALIBRATION R^2_{cal}	CALIBRATION $RMSE_{cal}$	PREDICTION R^2_{val}	PREDICTION $RMSE_{Val}$	SD	RPD SD/RMSEV	RPD category
MC	40	3,5,6,10,17,33	5	0,9658	0,2116	0,7337	0,6085	1,3685	2,2490	A
SOM	40	1,2,20,25,33,37	7	0,9891	0,2160	0,5901	0,1372	0,2427	1,7692	B
pH	40	1,8,9,21,24,36	6	0,9825	0,0233	0,7175	0,0967	0,2271	2,3482	A
Ntot	40	2,8,9,10,26,31	3	0,7769	0,0484	0,5126	0,0737	0,1120	1,5192	B
P	40	3,8,9,12,17,26	7	0,9921	0,0002	0,5432	0,0013	0,0019	1,4988	B
K	40	8,16,18,27,32,39	7	0,9929	0,0042	0,7580	0,0252	0,0507	2,0117	A
Fe	20	3,5,6,19	1	0,5664	0,7320	NA	1,8022	1,2231	0,6787	C
CEC	20	1,3,4,20	4	0,9693	0,5202	0,7260	1,6615	3,4465	2,0743	A
Texture										
SAND	20	3,7,15,16	5	0,9942	0,3467	0,6954	2,6709	4,3982	1,6467	B
SILT	20	3,10,16,20	6	0,9937	0,2790	0,4413	2,7989	3,5632	1,2731	C
CLAY	20	3,13,16,20	2	0,9991	0,0971	0,4089	2,6171	3,5734	1,3654	C

J. Map interpretation

There were about 62maps of 11 soil properties produced from 2 locations and 4 growth stages in this research. The range of soil property values was classified into certain defined interval value based on soil fertility criteria referred from Landon (1991) and Puslitannak (1993) [14]. The classification is listed in Tabel VI.

TABEL VI.
CLASSIFICATION FOR MAPPING THE SOIL PROPERTIES

No.	Property	Range	Interval value	Criteria
1	SMC (%)	11.0-17.5	2; 10 ~ 18	-
2	SOM (%)	0.6-1.8	0.5; 0.5 ~ 2.0	very low*
3	pH H_2O	6.7-7.7	0.5; 6.5 ~ 8.0	medium to high*
4	N total (%)	0.0-0.4	<0.1 ~ 0.2 ~ 0.5	very low to medium*
5	P_2O_5HCl (mg/100g)	6.5-25.5	<10 ~ 20 ~ 40	very low to medium**
6	K_2O HCl (mg/100g)	23-297	20 ~ 40 ~ 60 ~ >100	medium to very high**
7	Fe (ppm)	1.9-7.8	2; 0.0 ~ 8.0	deficiency: 2 ppm*
8	CEC(me%)	6.9-25.5	5 ~ 15 ~ 25 ~ 40	low to high*
9	Sand (%)	11.8-34.6	5; 10 ~ 35	-
10	Silt (%)	1.0-23.5	5; 0 ~ 25	-
11	Clay (%)	53.5-76.1	5; 50 ~ 80	-

source: * Landon, 1991; ** Puslitannak (1993) [14]

Some consistent patternsoccurred temporally and spatially from them. In this paper, two soil samples points were selected tostudy the correlation between the soil properties and their reflectances. For example at points G-25 and B-26, theirpositionat the reflectance curves(Fig. 4 and Fig. 5) were related to some parametersof soil property in certain time and space maps(Fig. 6 and Fig. 7).

It had been noticed that soil at G25, besides the whitish color soil, it also had very shallow topsoil over the bedrocks compared to surrounding soils. These conditions might cause differences in soil properties regarding moisture storage.Whitish soil color effect at the G-25 point was very strong to increase reflectance, but high moisture could reduce it.

The B-26 soil color was darker than the G-25, so the reflectance value was lower. The higher the moisture content, the soil looked wet or darker, so the reflectance value was lower. The increase in the value of the reflection of the soil in the sample G-25 followed by a decrease in the value of SOM. This pattern was not shown in the B-26 sample between phases, but indicated by the mean value, the higher SOM has lower reflectance. Darker soil might be influenced by a combination of SOM values and high moisture content which made the reflectance value lower.

During the rainy season, effective water utilization by growing vegetation was no more than 20% of the total rainfall [15].High amounts of rainfall that occur during vegetative growth are normally not beneficial unless soil water levels are extremely low before or after planting. Soybean requires the most water from flowering through seed fill [16]. Therefore, the soil moisture of the generative stage at Nglipar and Dlingo were decreased. The runoff over the terrace might be the factor that affected the decreasing of SMC, besides the increasing crop water requirement at the generative stage.

Soil moisture conditions have major effects on productive processes such as the accessibility, availability, uptake, and use of soil nutrients for crop growth and also on negative processes such as creating anaerobic conditions, and losses of nutrients from the soil [17].There are many factors affect the variability of SMC, for example, the texture and structure. Soil structure, texture, and depth determine the total capacity of the soil for storing available water for plant growth [18].

The soybean farm at Nglipar had been tilled using two wheels hand plow tractor before planting, while at Dlingo almost zero tillage had applied, that might cause the SOM at Nglipar was lower than at Dlingo.

Different treatment on fertilizing before planting might bring different result on the N total value in the soil at the next growth stages. The manure given before planting at Nglipar (G) was 2000 kg/ha, while at Dlingo (B) was only 750 kg/ha. Moreover, the steep terrace at B would carry away the fertilizer by runoff from the upper to lower place.

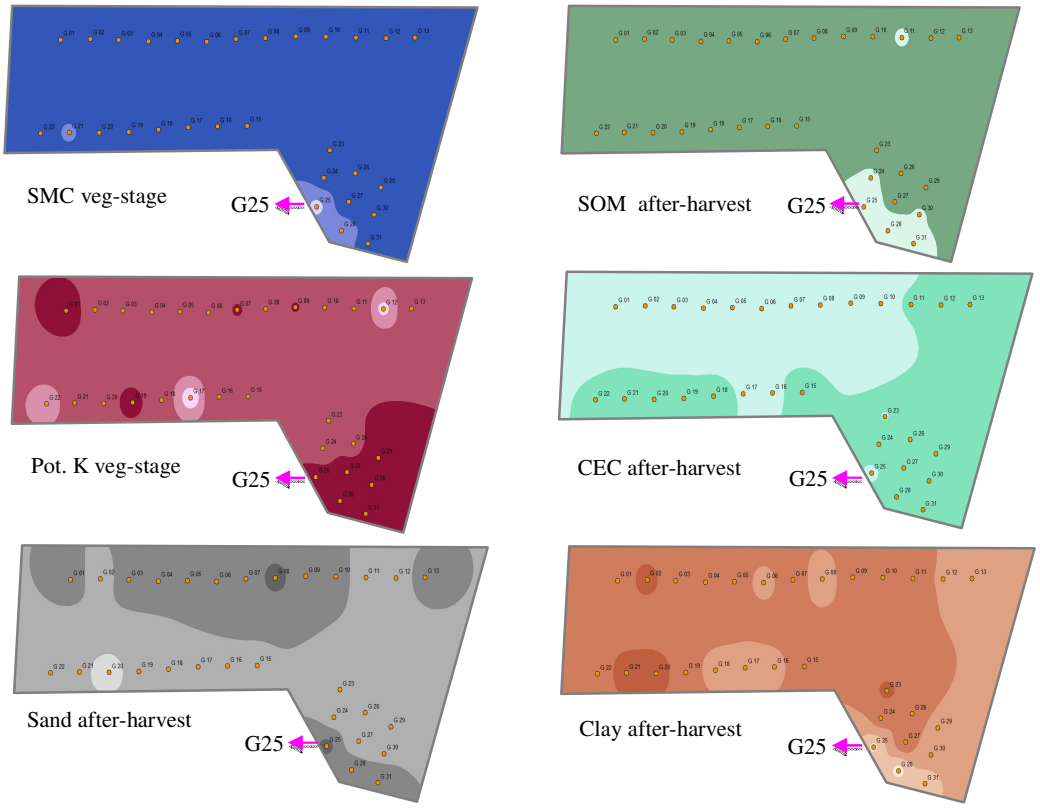

Fig. 6Some soil properties variability maps showing sample G-25 position

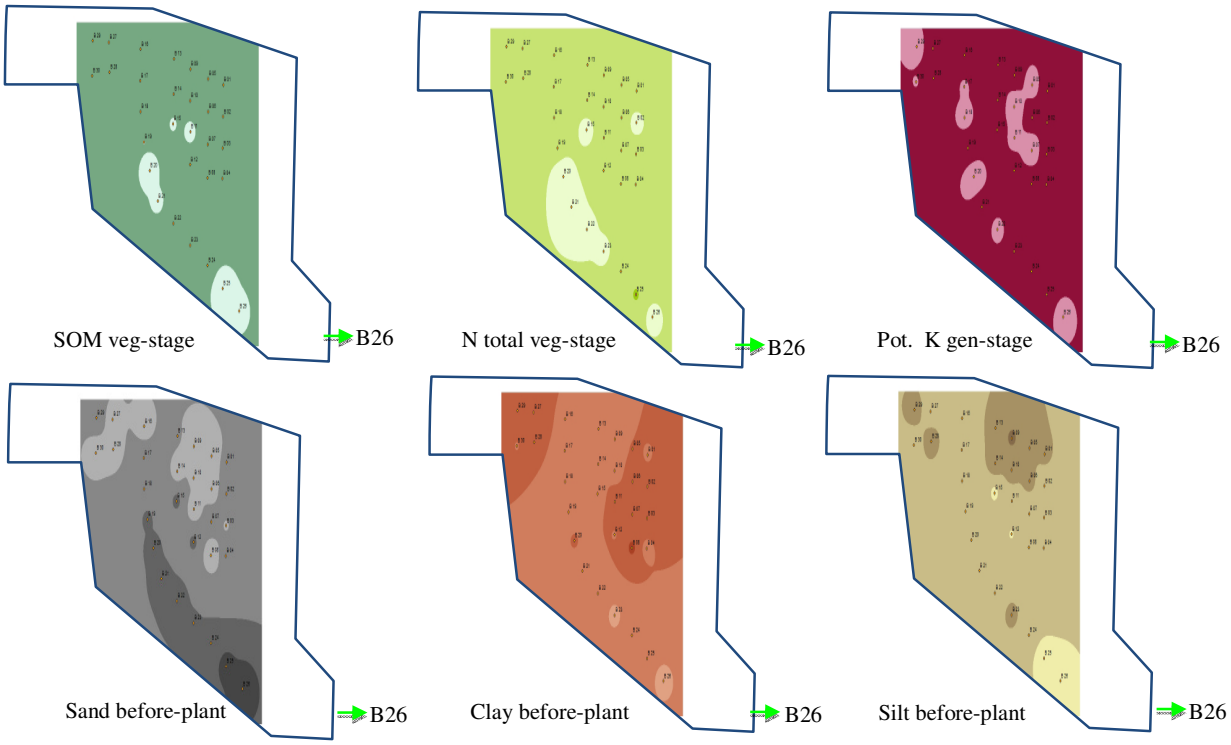

Fig. 7 Some soil properties variability maps showing sample B-26 position

IV. CONCLUSIONS

The models that had*excellent* performance in predicting soil properties were: SMC (Nglipar and Dlingo), pH (Dlingo),potential K (Nglipar and Dlingo), CEC (Dlingo), silt(Nglipar), and clay (Nglipar).

The models that had*good* performancewere: SOM (Nglipar and Dlingo),pH (Nglipar), total N (Dlingo), potential P (Dlingo), Fe (Nglipar), CEC (Nglipar), and sand (Nglipar and Dlingo).

Whereas the models that had *poor* performancewere: total N (Nglipar), potential P (Nglipar), Fe (Dlingo),silt (Dlingo), and clay (Dlingo).

It is still possible to get a better prediction model by *trial and error* process, namely by conducting a different pre-treatment for each soil property and determining the outliers that need to be removed from the data used for prediction.

Proximal soil sensing using Vis-NIR spectroscopy is a good tool for modeling soil properties that should be implemented in an area with high variability of soil type such as Indonesia.

ACKNOWLEDGMENT

We are grateful to The Ministry of Research, Technology, and Higher Education Republic of Indonesia for supporting our research with the Post Graduate Team Research Grant, and also to The UPN "Veteran" Yogyakarta Scholarship.

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