Mapping The Temporal and Spatial Variability of Soil Moisture Content Using Proximal Soil Sensing

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Abstract. In studies related to soil optical properties, it has been proven that visual and NIR soil spectral response can predict soil moisture content (SMC) using proper data analysis techniques. SMC is one of the most important soil properties influencing most physical, chemical, and biological soil processes. The problem is how to provide reliable, fast and inexpensive information of SMC in the subsurface from numerous soil samples and repeated measurement. The use of spectroscopy technology has emerged as a rapid and low-cost tool for extensive investigation of soil properties. The objective of this research was to develop calibration models based on laboratory Vis-NIR spectroscopy to estimate the SMC at four different growth stages of the soybean crop in Yogyakarta Province. An ASD Field-spectrophotoradiometer was used to measure the reflectance of soil samples. The partial least square regression (PLSR) was performed to establish the relationship between the SMC with Vis-NIR soil reflectance spectra. The selected calibration model was used to predict the new samples of SMC. The temporal and spatial variability of SMC was performed in digital maps. The results revealed that the calibration model was excellent for SMC prediction. Vis-NIR spectroscopy was a reliable tool for the prediction of SMC.

1. Introduction

Soils vary in space and time due to the combined effects of physical, chemical, and biological processes that operate at different scales and with different intensities [1]. Some soil properties are very stable, changing slightly by the time, such as texture and soil organic matter content. The other soil properties, such as nitrate (NO_3) and moisture content can fluctuate rapidly. Soil moisture is the major factor of the soil in plant growth. The gross effects of deficient and of excessive soil moisture on plant growth are well known. With irrigation and, where necessary with drainage, the farmer has the opportunity to exercise greater control over soil moisture than he does over any of the other soil physical factors [2]. Various measurable aspects of plant growth do not respond in the same manner to increasing moisture stress. The water that comes out of the ground system through evapotranspiration, drainage, and subsurface water flow, first had to interact with the soil and partly stored in it within a few moments up to many years. It is important to measure and monitor soil moisture to improve crop yield forecasting and irrigation planning. The problem is how to provide reliable, fast and inexpensive information of soil moisture in the subsurface or root zone from numerous soil samples and repeated measurement.

Gravimetric method is currently the most commonly accepted and most reliable method for soil moisture determination and calibration of all indirect measurement methods [3]. Despite its advantages of accuracy and high reliability, the gravimetric method is time and resource consuming, destructive, and unrepeatable. The development of sensing technology coupled with advances in information and communications technology is very supportive of the use of soil sensing. Soil sensing can facilitate the measurement and monitoring of the soil's physical and biochemical attributes to better understand their dynamics and interaction with the environment while considering their large spatial heterogeneity [4].

The proximal soil sensing (PSS) techniques have been developed to obtain georeferenced data on many soil parameters at different scales and times to better understand the variability [5]. Proximal soil sensing is field-based sensors to obtain signals from the soil when the sensor's detector is in contact with or close to (within 2 m) the soil [6]. The sensors provide soil information because the signals correspond to physical measures, which can be related to soils and their properties.

In precision agriculture, techniques such as diffuse reflectance spectroscopy and geostatistics are considered increasingly for the prediction of soil characteristics and to characterize within-field spatial variation [7]. Rossel et al. [8] demonstrated the potential of diffuse reflectance spectroscopy, using the VIS, NIR, MIR and combined spectra, and showed how qualitative soil interpretations might aid with the identification and assignment of spectral bands to soil constituents. The Vis-NIR real-time soil sensor also had great potential for determining the soil properties at 10, 15, 20 cm soil depth [9]. Vasques et al. [10] investigated the potential use of Vis-NIR diffuse reflectance spectroscopy to classify soils in areas with soil, geology, and topography that varied in southeastern Brazil from three depth intervals (0-20, 40-60 and 80-100 cm). This novel approach can improve soil classification and survey in a cost-efficient manner, supporting sustainable use and management of tropical soils.

The objective of this research was to develop calibration models based on laboratory Vis-NIR spectroscopy and partial least-square regression (PLSR) analysis to estimate the soil moisture content (SMC) at four different growth stages of the soybean crop in two small farms at Yogyakarta Province. The SMC was measured using the Gravimetric method, while the soil reflectance was scanned with an ASD Field-spec 3 (range from 350 nm to 2500 nm). The PLSR with full cross-validation was performed to establish the relationship between the SMC with the pre-treated Vis-NIR soil reflectance spectra. The selected calibration model was used to predict the other new samples of SMC. The temporal and spatial variability of SMC was 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 SMC. They were useful in supporting the process of decision making in field management.

2. Material and methods

2.1. *Site description*

The research was conducted at soybean farms in two locations, i.e. Natah Village, Nglipar District, Gunung Kidul Regency or G-field (7°51'39.0"S, 110°39'19.4"E) and Jatimulyo Village, Dlingo District, Bantul Regency or B-field (7°55'22.5"S, 110°29'08.7"E), in Yogyakarta Province (figure 1). The elevation of Nglipar ranges from 200 to 210 m asl., while Dlingo elevation ranges from 190 to 200 m asl. The slope varies between 5° to 10° which Dlingo was steeper than Nglipar. The variability of soil classification in the research area was high, even occurred in the same landform. 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* (table 1).

Nglipar and Dlingo had the tropical climate and classified as *Am* by Köppen and Geiger. The average annual temperatures of Nglipar and Dlingo were 25.2 °C and 25.8 °C, and the average rainfalls were 2,083 mm and 2,019 mm [11]. table 2 shows the average of monthly rainfall of the past 10 years. During the research, the monthly rainfalls from October 2016 to January 2017 were: 253, 526, 305 and 369 mm at Nglipar, and 232, 312, 420 and 411 mm at Dlingo [12].

Figure 1. Location of the research area:
G-field: Nglipar, Gunung Kidul Regency
B-field: Dlingo, Bantul Regency
(Source: Modified from Google Map 2017)

Table 1. Soil class and landform of Nglipar and Dlingo

Soil Class (Great group)	Proportion (%)	Landform	Parent material	Relief (% slope)
Nglipar, Gunung Kidul: Tectonic Group				
Hapludults	50-75	Undulated tectonic plain	claystone, sandstone	undulated (8-15)
Dystrudepts	25-50			
Dlingo, Bantul: Karst Group				
Hapludalfs	50-75	Karst hill	limestone	Small hilly (15-25)
Eutrudepts	25-50			
Udorthents	10-25			

Source: Indonesian Center for Agricultural Land Resources Research and Development (BBSDLP, 2016)

Table 2. The monthly rainfall average of 2007-2016 (mm)

Month / *Location*	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Nglipar(G)	314	334	277	190	123	79	53	38	117	80	219	496
Dlingo (B)	381	438	335	306	216	121	45	25	75	89	295	386

Source: BMKG, Sleman DIY (2017)

The activities and crop pattern in the farm at Nglipar and Dlingo were almost the same every year.

Table 3. The yearly crop pattern at Nglipar and Dlingo

Month / *Location*	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Nglipar(G)	GN	GN	GN	SB	SB	SB	-	-	-	SB	SB	SB
Dlingo (B)	SB/C	SB/C	SB/C	VB	VB	VB	-	-	-	SB	SB	SB

GN: Ground Nut; SB: Soy Bean; C: Corn; VB: Velvet Bean

2.2. *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 5 meter interval (figure 2). There were 30 sample points for each field marked with bamboo sticks. The soil was sampled 4 stages within one cropping season of soybean from October 2016 to January 2017, i.e., before planting (I), vegetative stage (II), generative stage (III) and after harvesting (IV). Soil at 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. 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. Eighty soil samples (10 x 2 x 4) were prepared for soil moisture analysis as the referenced parameter, and all 240 soil samples (30 x 2 x 4) were prepared for spectroscopic measurements as the predicted parameter.

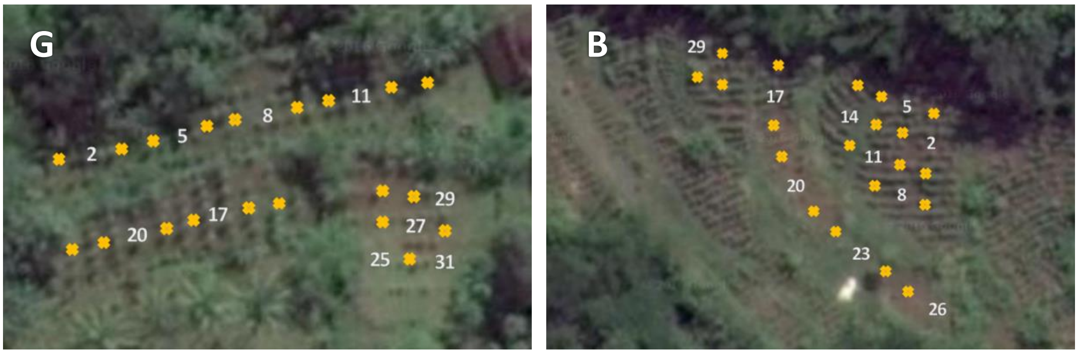

Figure 2. Field layout
left: Nglipar field (1,500 m^2), *right*: Dlingo field (1,300 m^2)
(Modified from Google Earth 2012)

2.3. *Soil moisture content analysis*

The soil moisture content was analyzed by the Soil Analytical Services Laboratory at UPN "Veteran" Yogyakarta using the Gravimetric method, i.e., calculates soil moisture by the difference between the fresh weight and dry weight of a given soil sample. A 40 g fresh weight subsample was taken from the soil sample of each plot was weighed and placed into a tin and then oven dried at 105^o - 110^o C for 24h. After drying the samples are reweighed.

2.4. *Laboratory Vis-NIR Spectroscopy*

The spectroscopy measurement was performed at the University of Palangka Raya, Central Kalimantan, using ASD Field-spec®3 350-2500 nm (Analytical Spectral Devices Inc., Boulder, Colorado, USA). Each soil sample was placed into a 5 cm diameter of 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 to hold the ASD probe of the optic sensors and keep the same distance from the probe tip to the sample surface (figure 3).

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

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The reflectance of each sample was scanned 10 times with different positions by moving the ring sample circularly, and the results were averaged in post-processing (figure 4). Every 15 minutes the instrument was calibrated by measuring the reflectance of the white panel as a white reference. The reflectance value of each spectrum was recorded in the computer and translated from binary to ASCII using *ViewSpecPro* software.

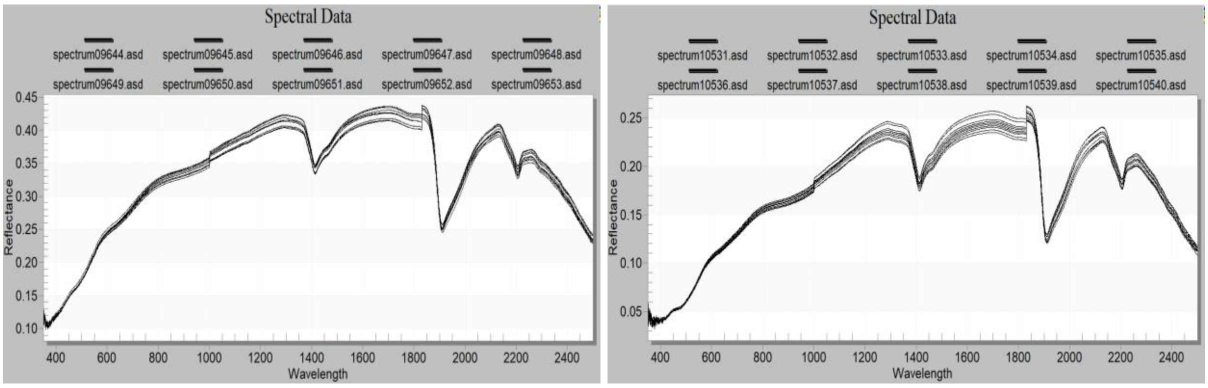

Figure 4. Examples of 10 times reflectance measurements from a soil sample (*left*: sample of G IV-25; *right*: sample of B III-15)

2.5. *Pretreatment, calibration and prediction process of spectral data*

The first step in developing the prediction models was the pretreatment of the spectral data. The process of pretreatment, calibration, and validation were performed using Unscrambler X software. The measured reflectance 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 [13]. 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 [14]. Moreover, both edges of the spectra were removed as these parts of the spectra were unstable and rich in noise [9].

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 amount of soil moisture content (reference values) with the pre-treated Vis-NIR soil absorbance spectra from the corresponding locations [9].

Two calibration models were developed, i.e., Nglipar (G) and Dlingo (B) SMC models. The models combined the dataset of 40 referenced SMC values (10 x 4) and the treated spectra of 600-2300 nm wavelength for each SMC model. In the PLSR analysis, sample outliers were detected by checking the residual sample variance plot after the PLSR. Individual sample outliers located far from the zero line of residual variance were considered to be outliers and excluded from the analysis. Due to the small number of data set for calibration (40 samples), the number of outliers was limited to maximum 6 samples.

The selection criteria of any pretreatments were the largest coefficient of multiple determinations (R^2) 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 NIRS to predict values of soil properties can be grouped into three categories based on RPD values: category A or excellent (RPD $\geq$2.0), category B or good (RPD = 1.4~2.0), and category C or unreliable (RPD <1.4) [15]. RPD was given by the ratio of standard deviation (SD) of the reference dataset to the root mean square error of full cross-validation ($RMSE_{val}$), as in equation (1) [9].

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

Each selected calibration model was used to estimate the moisture value of the new samples in associated location.

2.6. *Mapping the temporal and spatial of SMC variability*
The support of GIS is very helpful in giving visual information to support the decision making in the management of site-specific farming. In this research, the ArcGIS Ver. 10.2 software was used to perform the temporal and spatial of SMC variability maps. The inverse distance weighted (IDW) method was applied to do the spatial interpolation.

3. Results and discussion
To generate spectrum data, radiation containing all relevant frequencies in the particular range is directed to the sample. The radiation will cause individual molecular bonds to vibrate, and they will absorb light, to various degrees, with a specific energy quantum corresponding to the difference between two energy levels. As the energy quantum is directly related to frequency, the resulting absorption spectrum produces a characteristic shape that can be used for analytical purposes [16].

The soil has an easily distinguishable characteristic reflectance pattern in the visible, near-infrared and mid-infrared wavelengths [17]. Water has a strong influence on vis-NIR spectra of soils. The dominant absorption bands of water around 1400-1900 nm are characteristic of soil spectra [18]. Water also reduces the reflectance of regions in the short-wave infrared, particularly around 900, 1400, 1900 and 2200 nm [19].

3.1. *Soil properties description*
There were 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 [2]. Clay soils hold large amounts of nutrients and water tightly, slow infiltration or high runoff means much erosion and may shrink/swell, depends upon the type of clay minerals present [20]. table 4 describes the properties of the soil used in this study. The soil properties of all 80 samples were classified as *clay* with very low organic matter content (SOM) and moderate cation exchange capacity (CEC).

Table 4. Properties of the soils at research area

Property	Clay (%)	Sand (%)	Silt (%)	pH	SOM (%)	CEC (me%)
Nglipar	64.33	22.04	13.63	07.22	0.98	16.92
Dlingo	69.09	22.67	8.24	07.09	1.10	20.06

The landform such as terraced field is also affecting the SMC. Soil moisture amount was greater in terrace channels as compared to terrace intervals [21]. Research in terrace land showed that rainfall significantly affected the temporal stability of soil water storage in the depth of 0–0.6 m and increased from the upper to lower slope [22].

Both farmers at Nglipar and Dlingo used the same variety of Soybean (Grobogan) which was ready to harvest about 80 days. They grew the soybean at the rainy season from October 2016 to January 2017, and soils were sampled before planting (October 28), at vegetative stage (November 14), at generative stage (December 1) and after harvesting (January 19). During the research, the monthly rainfalls from October 2016 to January 2017 were: 253, 526, 305 and 369 mm at Nglipar, and 232, 312, 420 and 411 mm at Dlingo.

Rainfall was the only supply for the crop water requirement in these farms. High amounts of rainfall that occur during vegetative growth are normally not beneficial unless soil water levels are extremely low before or after planting [23]. Soybean requires the most water from flowering through seed fill. By considering other factors affecting evapotranspiration, the SMC information given in figure 5 could contribute to predicting the crop water requirements based on growth stages. Therefore, the actions to maintain water needs can be decided properly before the next stage.

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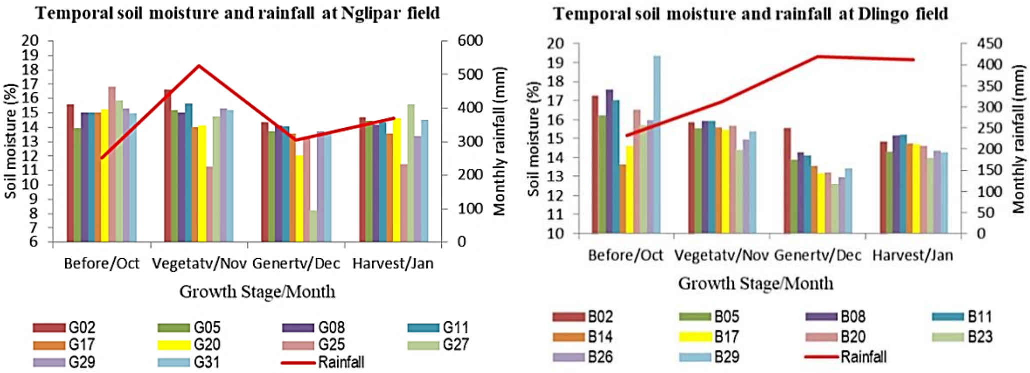

Figure 5. Soil moisture of 10 referenced samples at different stages and locations

Eighty graphs (10 x 2 x 4) from the total of 240 soil spectral measurements are shown in figure 6 and 7.

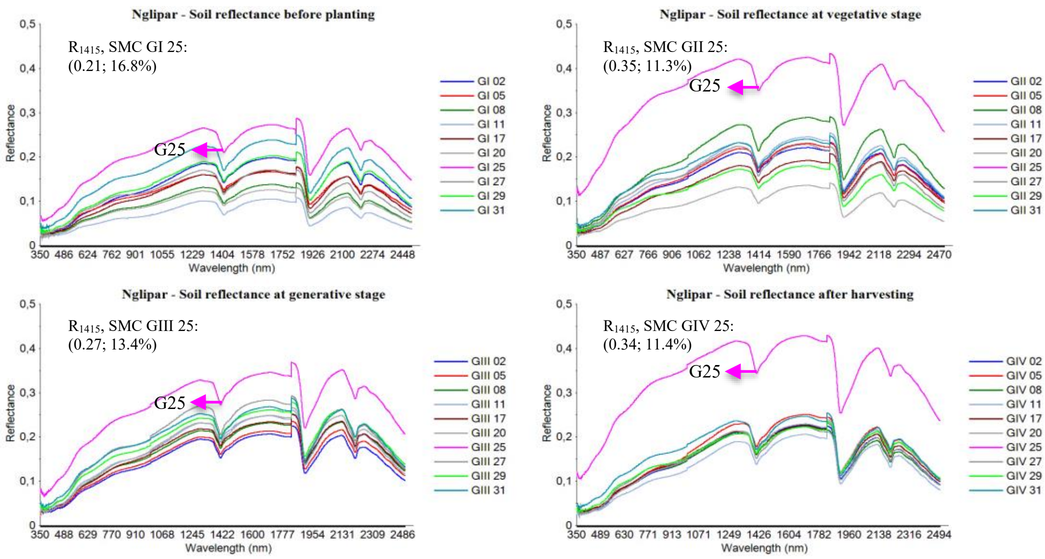

Figure 6. The soil reflectance of 10 referenced samples at different stages in Nglipar (G)

Soil reflectance can be influenced by some factors, such as soil texture, surface roughness, organic matter content, color and moisture content [3]. Field soil reflectance is reduced, particularly in the visible portion of the spectrum, when the moisture content is high [17]. Soil moisture and organic matter increase soil absorbency and result in overall lower soil reflectance [19]. To study the correlation between the soil reflectance, SMC, and growth stage. The sample G25 (figure 6) and B26 (figure 7) at about 1415 nm wavelength were picked for examples (table 5).

Table 5. The example of correlation between soil reflectance (R), soil moisture content (SMC) and growth stage at 1415 nm wavelength

Sample point	G 25 (Nglipar farm)		B 26 (Dlingo farm)	
Parameter	R_{1415}	SMC (%)	R_{1415}	SMC (%)
Stage I	0.21	16.8	0.15	15.9
Stage II	0.35	11.3	0.17	14.9
Stage III	0.27	13.4	0.19	12.9
Stage IV	0.34	11.4	0.18	14.3

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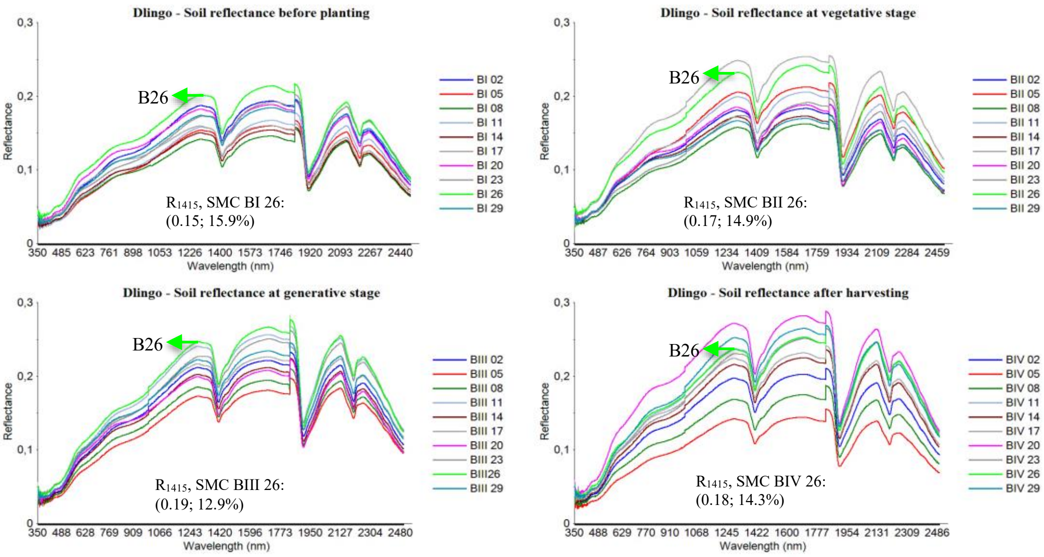

Figure 7. The soil reflectance of 10 referenced samples at different stages in Dlingo (B)

The increase of soil reflection values on samples G25 and B26 followed the decline of SMC. The effect of whitish color at G25 was strong to increase the reflectance, however high moisture might lower it. The soil color of B26 was darker than G25, so the reflectance value was lower. The higher the SMC, the wetter or darker the soil so the reflectance value was lower.

3.2. *Multivariate Statistical Analysis*

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). PCR and PLSR techniques can cope with data containing large numbers of predictor variables that are highly collinear [16]. 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.

There were four steps of pretreatment to the spectral data before proceeding them for calibration to enhance weak signals and remove noise due to diffuse reflection, i.e.:

a. Spectroscopic transform: reflectance to absorbance
b. Derivative Savitsky-Golay transform: second derivative and 2 polynomial order
c. Remove both edges of the spectra (<600 nm and > 2300 nm)
d. Convert spectral data from 1 nm interval to 10 nm interval.

The statistical descriptions of SMC data for calibration process are shown in table 6. The SMC at Nglipar ranges from 8.25 to 16.80%, with a mean value of 14.28%, while the SMC at Dlingo ranges from 12.60 to 19.34%, with a mean value of 15.03%.

Table 6. Descriptive statistics of soil moisture content data

SMC	Sample	Mean	Max	Min	Range	SD	Var.	RMS	Skew
Nglipar	40*	14.28	16.80	8.25	8.55	1.52	2.31	14.36	-18.41
Dlingo	40*	15.03	19.34	12.61	6.73	1.37	1.88	15.09	0.76

* from 10 referenced samples x 4 stages

The summary of developing calibration models for SMC using PLSR method and the RPD category are shown in table 7.

Table 7. Summary of PLSR results for SMC calibration models

PLSR results	Nglipar (G) SMC model	Dlingo (B) SMC model
Calibration samples	40	40
Prediction samples	120	120
Optimal factors	3	5
R^2_{cal}	0.76	0.97
$RMSE_{cal}$	0.50	0.21
R^2_{val}	0.61	0.73
$RMSE_{val}$	0.66	0.61
SD	1.52	1.34
RPD (SD/ $RMSE_{val}$)	2.32	2.25
RPD Criteria	A (excellent)	A (excellent)

The Vis-NIR predicted values using PLSR for SMC are described as regression models in figure 8. The data points of the measured moistures (reference) and the predicted are indicated excellent model performance (RPD > 2). The two soils measured by the Vis-NIR reflectance sensor and by the gravimetric method are compared, and they are highly correlated (R^2 = 0.76 and 0.97).

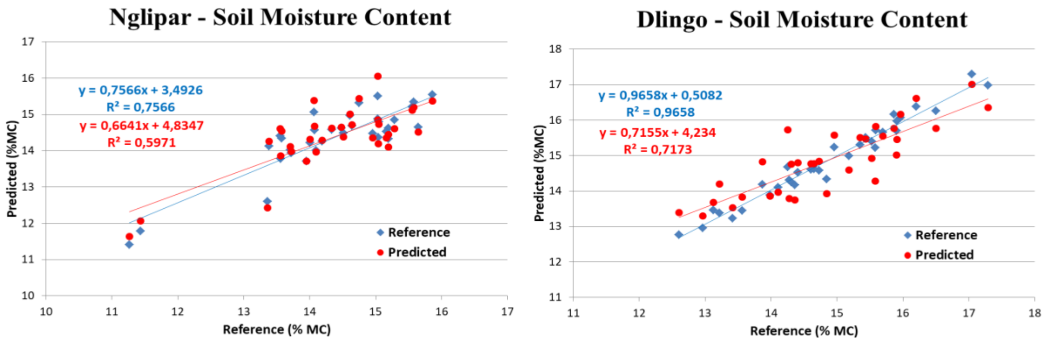

Figure 8. The regression model of soil moisture content at Nglipar and Dlingo

The better results obtained by using the PLSR method are clearly because PLSR takes advantage of the use of the entire spectral signature [24]. The regression coefficient plotted in figure 9 shows the investigated spectrum that should be considered important for the prediction of SMC. The size of the regression coefficients represents the importance of the absorption band.

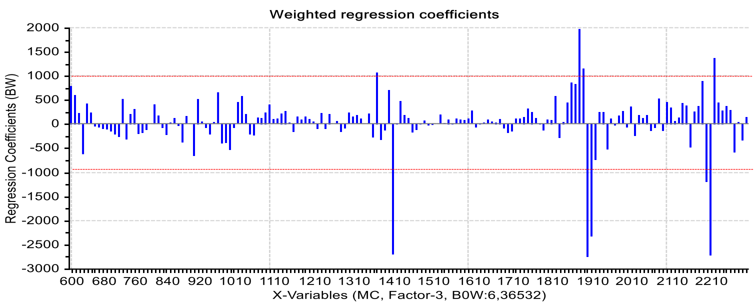

Figure 9a. The regression coefficients of SMC model for Nglipar (G)

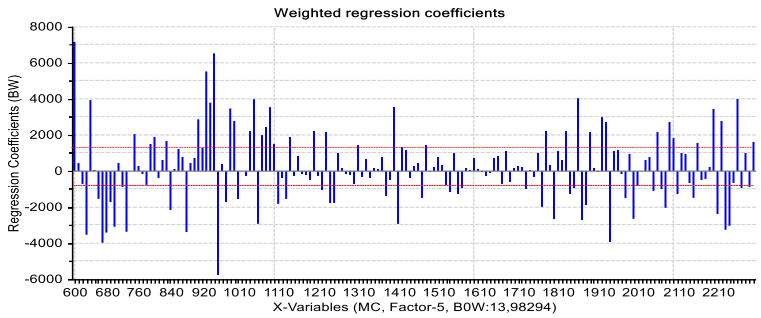

Figure 9b. The regression coefficients of SMC model for Dlingo (B)

3.3. *Temporal and spatial map of SMC variability*

The prediction value of SMC was then applied to generate the temporal and spatial map of SMC. The inverse distance weighted (IDW) method was applied to do the spatial interpolation. figure 10 and 11 show the SMC variability map of Nglipar and Dlingo for each stage. The SMC at Nglipar of all stages were dominantly about 14-16% and a small part about 12-14% at the generative stage. The SMC of G25 at vegetative stage and after harvesting were the lowest (11%). 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.

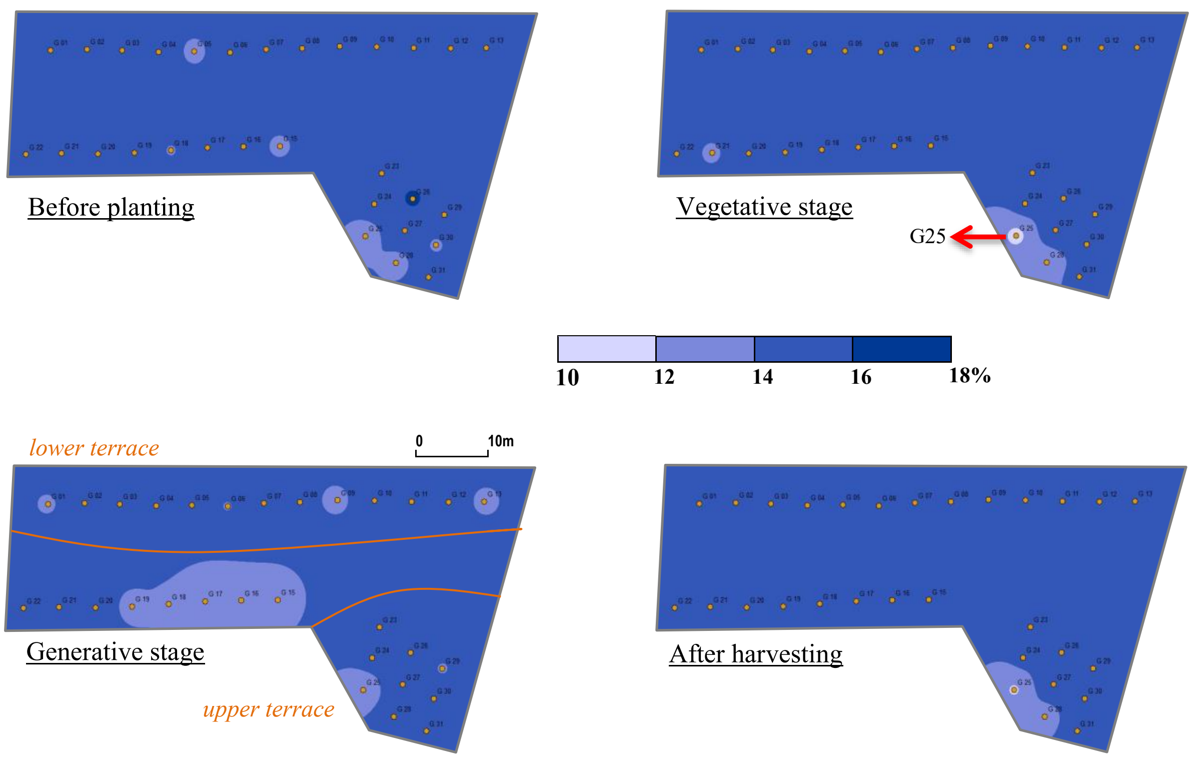

Figure 10. The temporal and spatial map of SMC variability at Nglipar (G)

The SMC at Dlingo was more varied than at Nglipar with the range from 12 to 18%. The SMC decreased gradually from before planting to the generative stage. 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.

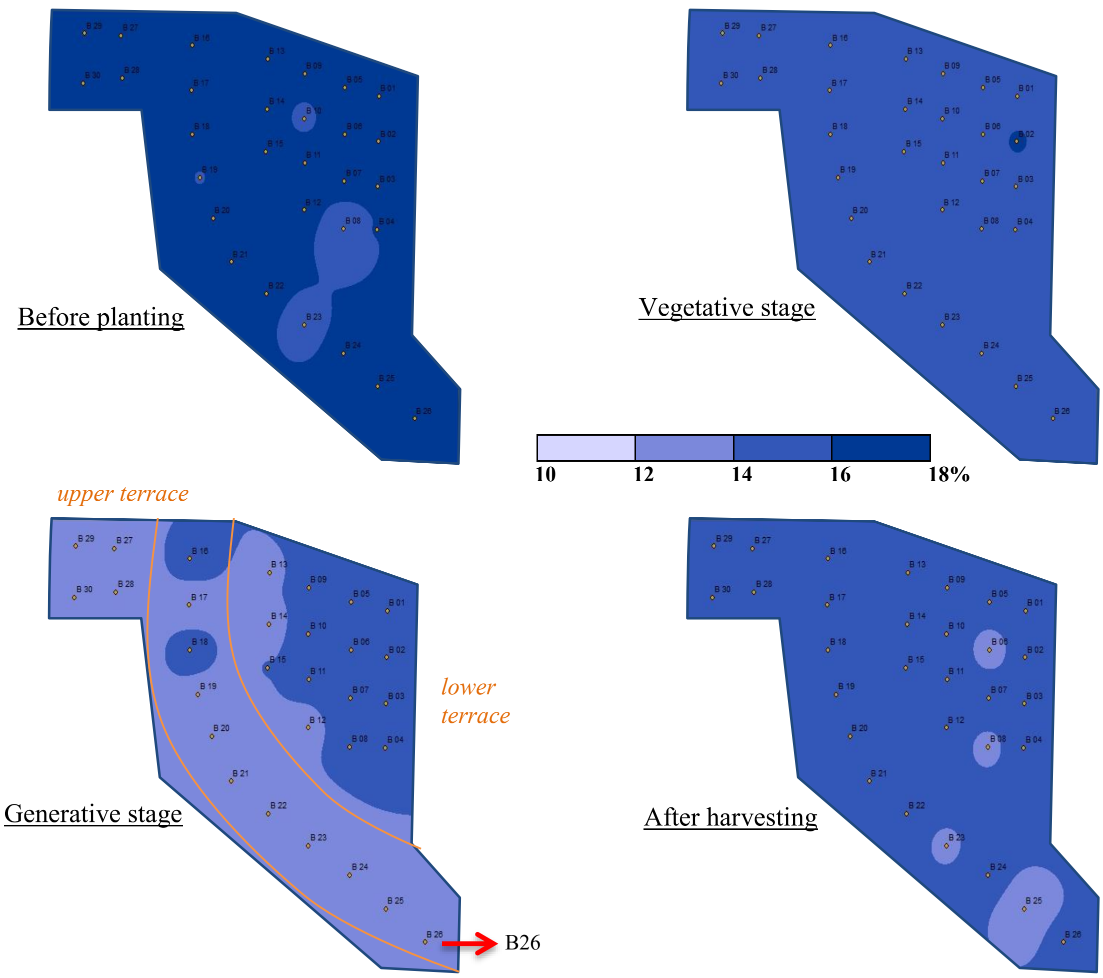

Figure 11. The temporal and spatial map of SMC variability at Dlingo

4. Conclusions

The performance of Vis-NIR reflectance spectroscopy to estimate soil moisture content (SMC) using PLSR method resulted in satisfactory level. It was proven from the RPD values that the calibration models were "excellent" to predict SMC. Dlingo prediction model had higher accuracy compared to Nglipar. In this study, soil proximal sensing using Vis-NIR spectrum was a reliable tool for the prediction of SMC of unknown soil samples. Different pretreatment process should be performed to improve the correlations between the measured soil moisture content and the spectra. The temporal and spatial maps of SMC variability gave much information to be interpreted carefully due to many factors affect the SMC. They were useful in supporting the process of decision making in field management.

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