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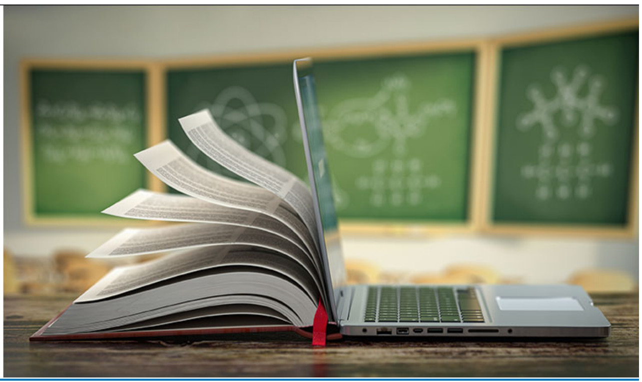

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The stability of calibration model in measuring and mapping soil organic matter in a dry climatic area

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Abstract. The increase of atmospheric CO_2 concentration from soil organic matter (SOM) decomposition may contribute to the global warming and climate change. So, sequestering this greenhouse gas into SOM may be used to mitigate climate change. However, tedious procedures in measuring and mapping SOM need to be replaced with a method which works based on the reliability of calibration model developed. This research aimed to test the reliability of the calibration model that was built from a separate soil sample group to be used to measure and map SOM on other validation soil sample group, in the mostly dry climatic area of Kayangan Sub-district, North Lombok Indonesia. For this purpose, 300 soil samples were collected from the area using grid method, which were then dried, ground, sieved, analysed for SOM content using the Walkley and Black method, and scanned using Near Infrared Spectroscopy. The model built using calibration sample group was able to reliably measure and map the SOM content of the spectral data collected from the validation sample set. This is shown by the coefficient of determination (R^2_V= 0.79), root mean square error ($RMSE_V$ = 0.246%) and the ratio prediction to deviation (RPD_V = 2.09). SOM maps generated from both laboratory and near infrared method can show very low, low and medium SOM content. These maps can be further used as a reference for applying organic fertilizers, avoiding excessive use of fertilizers, and monitoring soil carbon sequestration in mitigating climate change.

1. Introduction

Increasing the concentration of carbon dioxide (CO_2) in the atmosphere contributes to global warming and climate change [1]. Although the global warming potential of CO_2 is much lower than methane (CH4) and nitrous oxide (N_2O), the concentration of CO_2 in the atmosphere is the highest compared to the other two anthropogenic greenhouse gasses [2]. CO_2 emission from the soil is partly derived from the decomposition of soil organic matter (SOM), where soil respiration is reported to be one of the largest contributors [3]. Many efforts have been tried to reduce this greenhouse gas from the atmosphere, and capturing this gas through plant photosynthesis proses and storing the organic carbon as soil organic matter (SOM) is considered to be the simple option in mitigating climate change [4].

From the soil science perspective, SOM is one of the primary factors in determining soil fertility and land productivity [5], as it influences the physical, chemical, and biological properties of soil [6]. SOM can improve soil aeration, soil aggregate stability, and increase soil water holding capacity [7]. It can increase the availability of macro and micronutrients through organic matter decomposition, increase the soil's cation exchange capacity (CEC), and act as a buffer against changes in soil pH [8]. SOM can also support the biodiversity of organisms in the soil which play a very important role in supporting the nutrients cycle in the soil [9].

Considering the varying amount of SOM in the soil, there is a tendency for its amount to decrease, especially in a dry climatic area [10] which is predicted happening in a dry climatic area of Kayangan Sub-district North Lombok. This area is characterised by porous sandy soil, low clay content, low annual rainfall where some areas are less than 1250 mm per year, and some areas are planted only once a year causing less accumulation of organic residue in the soil [10]. Proper management of SOM is needed, especially the addition of SOM on land with very low SOM content. Ironically, the practice of applying organic fertilizers so far generally does not use a reference of SOM map. This creates difficulty to apply the right dose of organic fertilizer at the right location [11]. Ideally, more organic fertilizer should be applied in areas with very low SOM content, and vice versa [12], so that the effectiveness of SOM application and the improvement of soil properties can be achieved, and the negative environmental impacts as well as the wasteful use of SOM can be avoided [13].

Although SOM map is crucial as the fertilizer application guidance, their availability is very rare due to the high cost of conventional SOM analysis [14]. Besides being expensive, it also takes a long time for the analysis process. However, with the emerging of near infrared (NIR) technology, this problem can be overcome, as it does not require chemical reagents in the operational process [15]. This technology makes use of the covalent bonding of small atoms (such as C-H, N-H, and O-H) which is then linked to the SOM content of the soil [16], [17]. This NIR technology has been proven to be able to quickly and accurately measure the SOM content of soil [18], [19], [20].

However, what is still a challenge is how to build and produce a reliable (robust) calibration model, so that it is not necessary to carry out chemical analysis in the laboratory which takes a long time and is expensive. Once a reliable calibration model is found, it can be used to measure or predict the SOM content for later times, thus saving time and cost of making maps. For this reason, this study aims to test the reliability of the calibration model that is built from a separate calibration sample group to be used to measure and map SOM on the other validation soil sample set, in the mostly dry climatic area of Kayangan Sub-district, North Lombok, Indonesia.

2. Materials and methods

2.1. Determination of coordinates, collection of soil samples, and their analysis

The coordinates of the 300 sampling positions were determined using the grid method on the map of Kayangan Sub-district, North Lombok, Indonesia [21]. Then, 300 soil samples (0-10 cm depth) were collected using a soil corer at the pointed coordinates of the study area. All samples were then transported to a laboratory to be dried, ground, and sieved (0.2 mm of sieve diameter). The soil samples were separated into two parts, subsequently each part was analyzed for SOM content using the Walkley and Black method, and scanned using Near Infrared Spectroscopy (NIRS) [22].

2.2. Pre-processing of soil spectral data

The reflectance of all soil spectral data ranged from 350 to 2500 nm were captured using a contact probe from the ASD FieldSpec 3 V-NIR Spectrometer (Analytical Spectral Devise, Boulder, CO, USA). Soil spectral data were then imported into ParLeS software [23] for spectral pre-processing (transforming spectral data to log(1/R), de-trending, smoothing using the Savitzky-Golay filter, transforming to the first derivative, and then mean centering) [24], [25].

2.3. Testing the accuracy of calibration model and creating SOM map

A partial least square regression (PLSR) calibration model was built using two-third of Walkley and Black analyzed SOM data and the 750-2500 nm of pre-processed spectral data (200 samples). The ability of this model to predict the SOM content was then tested on one-third of the remaining spectral data (100 samples) in the validation sample set. To avoid overfitting of the calibration model, the PLSR model was built using many principal components which resulted in the lowest root mean square error (RMSE) and the lowest value of Akaike Information Criterion (AIC) [23]. The stability of the calibration model was determined using the following parameters; the highest coefficient determination in validation (R^2_V), the lowest $RMSE_V$ in validation, and the highest ratio of prediction to deviation in validation (RPD_V) [26], [27]. Then the maps of SOM resulted from Walkley and Black and NIRS method were developed using ArcGIS geostatistical analysis (kriging) by involving the coordinates of the soil samples and SOM data of both methods.

3. Results and discussion

3.1. SOM content at the research location

The SOM data in the study area are presented in Table 1. The SOM status varied from very low to moderate, with an average of low status. This is probably due to the small amount of organic matter residue left after crop harvesting. Some parts of the research areas which were not planted intensively could produce little biomass, as a result small amount of SOM residue may be left in the soil [10]. Some other parts which were rain-fed areas and planted only once a year may result from low below-ground biomass production [10].

Table 1. SOM content in the study area.

Soil properties	**Range**		**Median**	**Mean**	**Standard deviation**	**Variance**
	Min.	Max.				
Soil organic matter (%)	0.67 Very low	3.93 Medium	1.73 Low	1.78 Low	0.52	0.28

3.2. The important bands of the calibration model

The PLSR coefficient model built from two-third of laboratory and spectral data can be seen in Figure 1. The PLSR coefficient values vary from negative to positive. The greater coefficients, either negative or positive at certain wavelengths, show a greater role in the model for determining SOM [28]. These wavelengths are around 980 nm and between 1900 and 2500 nm. Conversely, if the coefficient values are close to zero, their role is getting smaller.

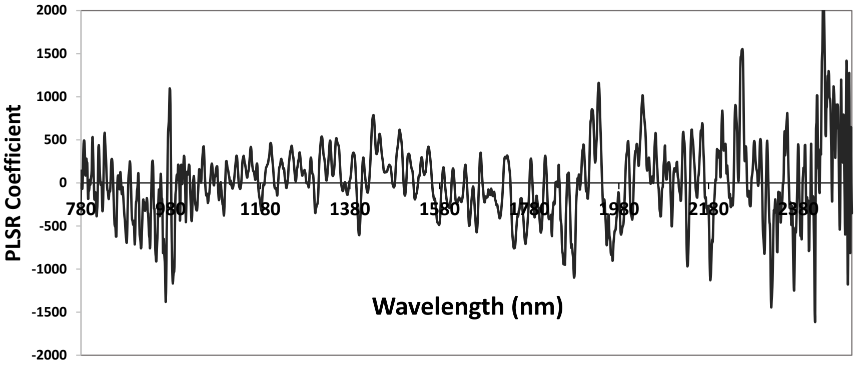

Figure 1. The PLSR coefficients of calibration model.

More important wavelengths in determining SOM predictions can be seen not only from the PLSR coefficients but also from the VIP (very important prediction) values [22] (Figure 2). Unlike the PLSR coefficients which have negative values, all the VIP values are positive. The greater the VIP values at a certain wavelength, the bigger their role in predicting SOM content [22]. Similar to the PLSR coefficients, larger VIP values are seen at wavelengths around 980 nm and between 1900 and 2500 nm.

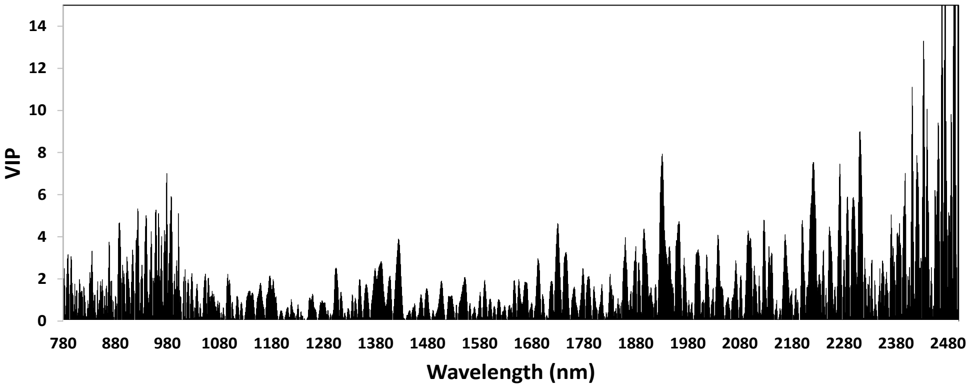

Figure 2. VIP bands at wavelengths of 780-2500 nm.

3.3. The stability of calibration model

The accuracy of the calibration model to predict SOM in the validation sample set can be seen in Table 2. By using a NIR wavelength (780-2500 nm) and a PLSR factor of 12, the calibration model succeeded in predicting SOM with moderately accurate results. This is indicated by the R^2_V, $RMSE_V$, and RPD_V values listed in the table. Some previous workers reported successful calibration models when the R^2_V is higher than 0.8 and RPD is bigger than 2.0 [29], [30]. If the calibration model is reliable enough, then it can be used to quickly calculate SOM from unknown soil samples without analytical measurements in the laboratory, which then greatly saves time, labor, and money.

Table 2. The model accuracy in predicting SOM.

Soil Properties	**Wavelength used**	**PLSR factor used**	**Validation**		
			R^2_V	$RMSE_V$	RPD_V
Soil organic matter	NIR (780-2500 nm)	12	0.79	0.246	2.09

The relationship between SOM measured by Walkley and Black method and predicted by NIRS is presented in Figure 3. With a coefficient determination (R^2_V) 0.79 and ratio prediction to deviation (RPD_V) 2.09 between SOM measured by laboratory and predicted by NIRS, this shows that the NIRS method has relatively similar accuracy in predicting SOM as the Walkley and Black method. Both Chang et al. [29] and Malley et al. [30] classified this accuracy into moderate. Many factors can affect the accuracy of near infrared technology, such as the accuracy of analytical analysis in the laboratory, the presence of outliers in modeling [19], and other factors such as water content, decomposition stage of organic matter, clay and non-clay minerals in the soil, iron oxides, carbonate, and soil particle size differences [31].

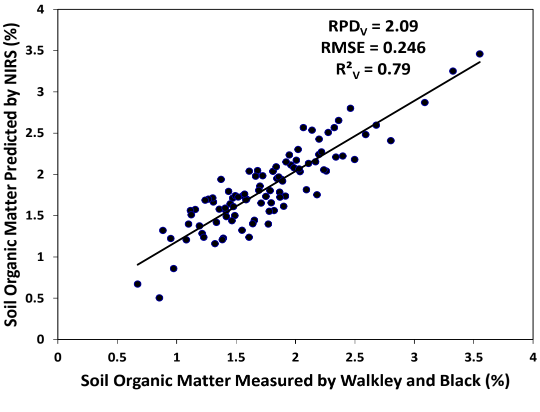

Figure 3. Relationship between SOM measured by Walkley and Black and predicted by NIRS.

3.4. SOM map

The SOM map generated from SOM data measured using the Walkley & Black method and predicted using the PLSR model can be seen in Figure 4. In general, both maps can describe locations having very low to medium content of SOM; very low SOM content is showed by brighter colors, while medium SOM is showed by darker colors. The ability of NIRS to quickly measure and map the SOM provides an opportunity for measurement and monitoring of this soil property more quickly. Knowing rapidly the status of SOM in particular locations will easy to manage the SOM based on the specific location [12]. For example, in areas with very low to low SOM content, it is necessary to add more SOM such as organic fertilizers, and or to apply soil management which accelerates SOM accumulation. The rapid production of SOM map may also be rapidly used to monitor the soil health and quality, to monitor the capacity of soil in sequestering carbon, and the role of soil in mitigating climate change.

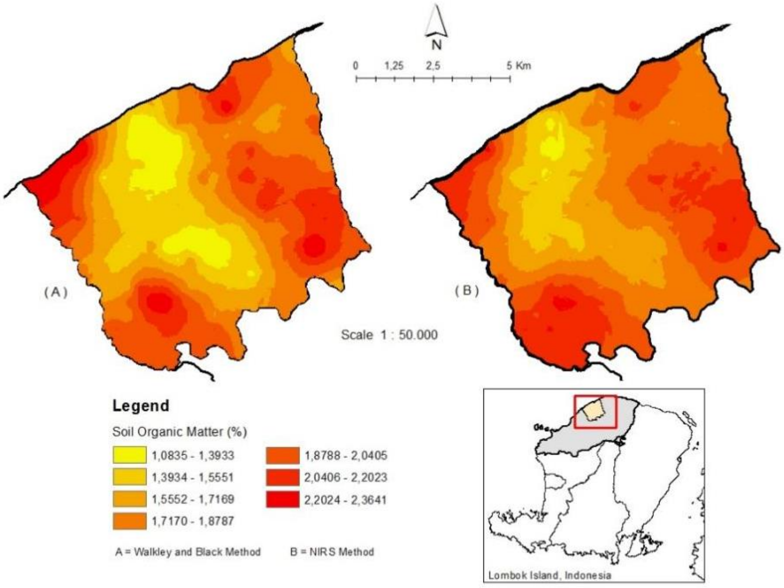

Figure 4. SOM maps resulted from (A) Walkley and Black method, and (B) NIRS method.

4. Conclusion

The PLSR calibration model for predicting SOM content in a dry climatic area of Kayangan Sub-district North Lombok Indonesia is relatively stable. The calibration model was able to reliably measure the SOM content from the validation sample set, which is indicated by quite high R^2_V, small $RMSE_V$ and reasonably high RPD_V. The distribution of SOM on the map resulted from NIRS-predicted SOM is relatively similar to the SOM map resulted from Walkley and Black method. Both maps identify very low to moderate SOM content at quite similar locations. These maps can be further used as a reference for applying organic fertilizers, avoiding excessive use of fertilizers, and monitoring soil carbon sequestration to mitigate climate change.

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