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The rapid measurement of soil carbon stock using near-infrared technology

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Abstract. As a soil pool stores carbon (C) three times higher than an atmospheric pool, the depletion of C stock in the soil will significantly increase the concentration of CO_2 in the atmosphere, causing global warming. However, the monitoring or measurement of soil C stock using conventional procedures is time-consuming and expensive. So it requires a rapid and non-destructive technique that is simple and does not need chemical substances. This research is aimed at testing whether near-infrared (NIR) technology is able to rapidly measure C stock in the soil. Soil samples were collected from an agricultural land at the sub-district of Kayangan, North Lombok, Indonesia. The coordinates of the samples were recorded. Parts of the samples were analyzed using conventional procedure (Walkley and Black) and some other parts were scanned using near-infrared spectroscopy (NIRS) for soil spectral collection. Partial Least Square Regression (PLSR) was used to develop models from soil C data measured by conventional analysis and from spectral data scanned by NIRS. The best model was moderately successful to measure soil C stock in the study area in North Lombok. This indicates that the NIR technology can be further used to monitor the change of soil C stock in the soil.

1. Introduction

A global soil pool stores about 1500 Pg carbon (C) that is approximately three times higher than that in an atmospheric pool [1]. The disturbance of this pool through leaching, soil erosion and respiration of soil organisms may cause soil C loss that may turn into CO_2 to the atmosphere, causing global warming [1]. C loss through respiration is predicted to be the largest loss [2]. Monitoring the soil C stock will be very useful in observing CO_2 flux to the atmosphere.

However, monitoring soil C stock using conventional procedures is time-consuming and expensive. Large numbers of soil samples have to be collected, transported to the laboratory, dried, sieved and analyzed with appropriate and systematic procedures. Tedious procedures of laboratory measurements take a long time in handling a large number of samples. So it requires a rapid technique that is simple and does not need chemical substances.

Near-infrared (NIR) technology has become an important analytical technique in recent years [3]. It works based on the vibration of covalent bonds of small atoms such as C-H, O-H, and N-H. Soil reflectance of near infrared is a complex spectrum and contains rich information of chemical and physical composition of materials [4,5]. This technique has been successfully able to measure or map soil C and N [6,7,8,9]. It is also able to measure soil moisture content, organic matter, CEC, total C, ammonium N, nitrate N, total N, available P, and P absorptive coefficient [10], root density [11,12,7], and biochar properties [13].

However, no information has been found related to the ability of this technique in measuring and mapping C stock in Indonesian soils. This study presents the ability of this technique to rapidly measure and map soil C stock in Kayangan sub-district, North Lombok, Indonesia.

2. Materials and methods

2.1. Soil sample collection, preparation and analysis

Topsoil (0-10 cm depth) from 305 locations were collected using soil corer (2.54 cm diameter) in Kayangan agricultural area, North Lombok, Indonesia (Figure 1). The coordinate of each sample was recorded, and then soil samples were transported to the laboratory to be dried (air dry), crushed and sieved to pass 0.2 mm diameter sieve. Part of each sample was analyzed for total soil C (Walkley and Black).

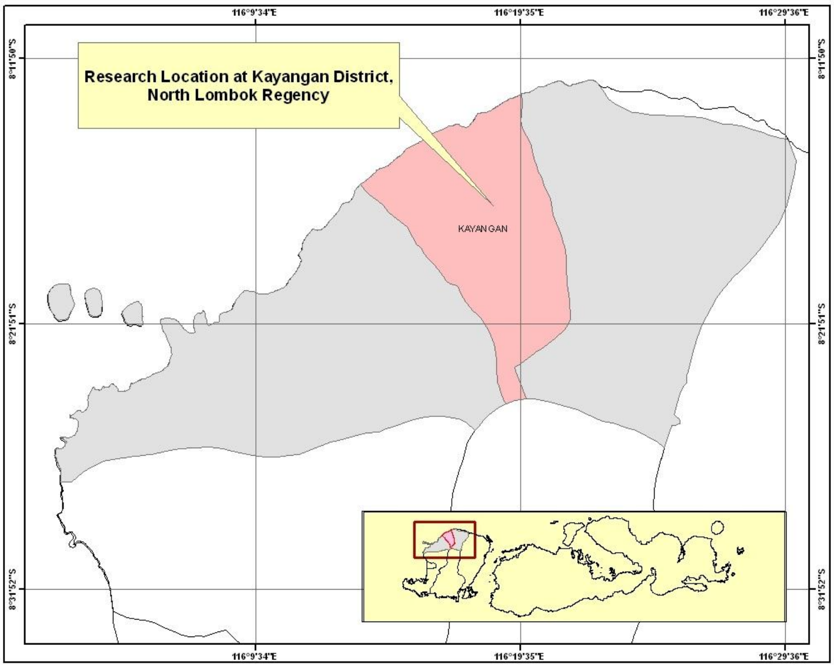

Figure 1. Location of soil sample collection.

2.2. Spectral acquisition and spectral pre-processing

Spectral reflectance (UV, visible and NIR range; 350 – 2500 nm) of another part of each sample were acquired using ASD FieldSpec 3 V-NIR Spectrometer (Analytical Spectral Device, Boulder, CO, USA). The spectral data were then imported into a software [ParLeS; 14] for spectral pre-processing namely: transformation to log (1/R) – R, wavelet detrending, and smoothing using a Savitzky-Golay filter. The smoothed data were thereafter processed into the first derivative, and then finally treated using mean centering [13].

2.3. Developing calibration models and parameters indicating accuracy of the model

Partial Least Square Regression (PLSR) was used to develop calibration models between the pre-processed spectral data and the reference analytical data of soil C. To avoid overfitting, the number of factors (principal components) that produce low root mean square error (RMSE) and low Akaike Information Criterion (AIC) were used to develop the models [14]. Then the models were tested using one-leave-out cross-validation. Afterwards, the ability of the PLSR models to predict soil C was assessed using the following statistics [13]: (i) RMSE (root mean square error) of measured and predicted soil C, (ii) coefficient determination (R^2), and (iii) RPD (ratio of prediction to deviation);

RPD is calculated as standard deviation of the reference data divided by root mean square error (SD/RMSE). The best prediction model is showed by the largest RPD and R^2, and the smallest RMSE.

3. Results and discussion

3.1. Summary of Soil Carbon

The summary of soil property (soil C) collected from Kayangan agricultural area, North Lombok, is shown in Table 1. The range (min-max) of soil C is narrow, from very low to medium, with no samples containing high C. Low content of C in this soil is probably related to the low return of organic matter and also due to coarse soil texture with low clay content. Soil with less clay and coarse texture has less ability to protect organic matter from biological degradation.

Table 1. Soil property.

Soil property	Range		Median	Mean	Variance	Standard deviation	Coefficient of variation (%)
	Min.	Max.					
Total C (%)	0.39	2.28	1.01	1.03	0.092	0.304	29.45

3.2. Soil Spectral Shape

As the C content is one of the most influential factors on the spectral shape, the soil spectral shape is shown based on the variation of C content (very low < 1% C; low 1-2% C; and medium 2-3% C) (Figure 2). Soil with very low C has a higher reflectance at around 750 nm compared to soils with low and medium C, showing a brighter color. Soil with higher C shows lower reflectance (darker color) at around visible band, indicating a higher amount of organic matter. Soil with very low organic matter content has a sharper angle at around 750 nm, compared to low and medium organic matter content; this was also found by Dematte et al. [15] and Kusumo et al. [6]. Strong absorption at around 1400 and 1900 nm (Figure 2) is the first overtones of the O-H bond of water and the combination of the H-O-H bend and O-H stretching, respectively [17]. Strong absorption at around 2200 nm is a combination of metal O-H bend plus O-H stretch [17].

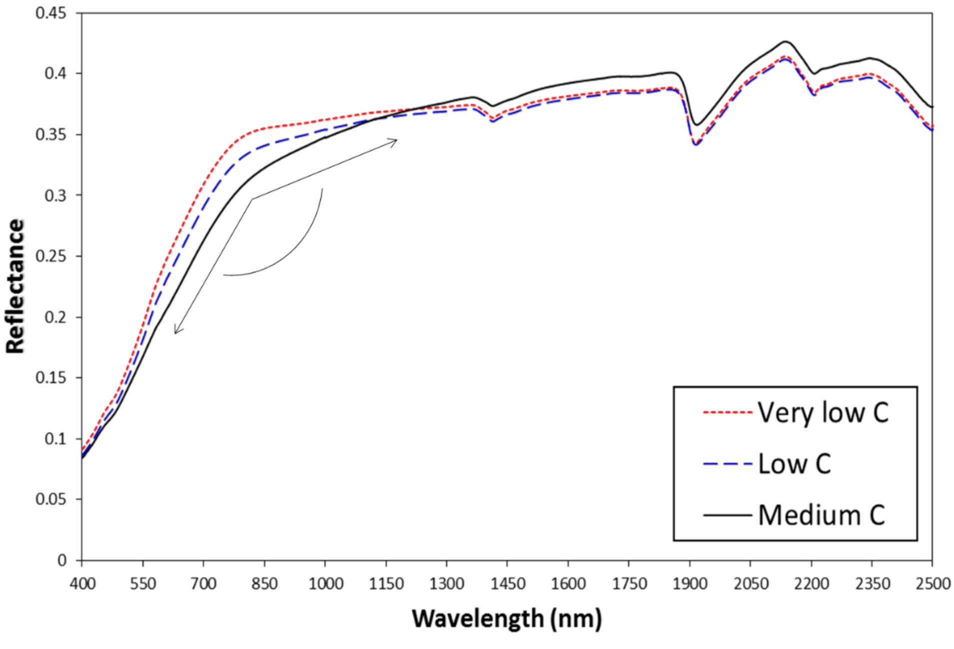

Figure 2. The spectral shape of soils with very low, low and medium amount of carbon.

3.3. Accuracy Measurement of Soil C using NIRS

Prediction values of soil C using leave-one-out cross-validation are shown in Table 2. NIRS technique was able to moderately predict soil C (RPD around 2.00). Both methods produce the average of soil C content 1.03%. According to Chang et al. [17], the prediction values of soil properties with R^2 0.5-0.8 and RPD 1.4-2.0 are considered moderately successful. While Malley et al. [18] considered moderate accuracy if the R^2 0.7 – 0.8 and RPD 1.75 – 2.25. Some factors may influence the accuracy of near-infrared prediction models, such as less accuracy of laboratory analysis as the reference data, spectral outliers or both. Other chromophores (such as water, decomposition level of organic matter, clay and non-clay soil minerals, carbonates, iron oxides, particle size) [19] may also influence the accuracy.

Table 2. Prediction values of soil C using leave-one-out cross-validation.

Properties	Prediction values (leave-one-out cross-validation)		
	R^2_{CV}	$RMSE_{CV}$	RPD_{CV}
C Total	0.756	0.151	2.01

The relationship between laboratory measurement and NIRS prediction of soil C is shown in Figure 4. The moderate accuracy of NIRS measurement on soil C (R^2_{CV} 0.75-0.76 and RPD_{CV} 2.00-2.01) shows that this technique may be used to measure and map soil C in the Kayangan agricultural area North Lombok. Some previous researchers also found the moderate accuracy of C measurement using NIRS technique [6,17].

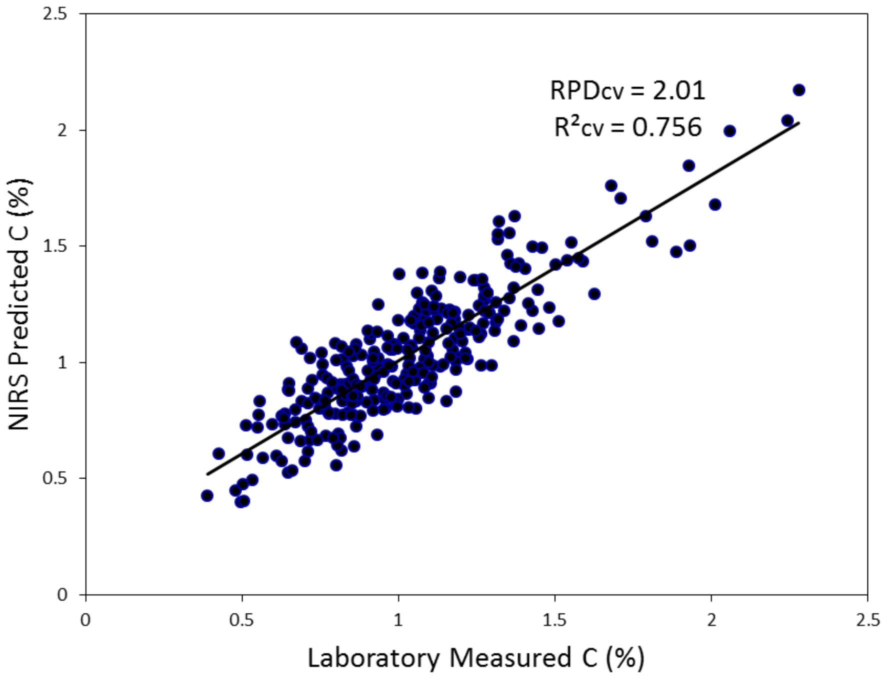

Figure 3. The relationship between laboratory measurement and NIRS prediction of soil C; from the C variation values, both methods produce the average of soil C content = 1.03%.

3.4. Successful Mapping of Soil Carbon

The map of soil C content produced from laboratory analysis and NIRS analysis is shown in Figure 5. It can be seen that soil C can be successfully mapped using NIRS technique. The map can show the degradation of the soil C content from lower (brighter blue color) to higher C content (darker blue color).

The successful mapping soil C using NIRS technique may benefit for the other purposes. The map can be used as a management tool for rapid monitoring the C stock in soil and for C sequestration strategy. It may also be used as a guidance in adding organic matter. It is suggested to add more organic matter in a location with a low soil organic matter content. It may be used as well as the information in mapping soil fertility status. The high fertile soil is shown by a high content of organic matter (soil organic C).

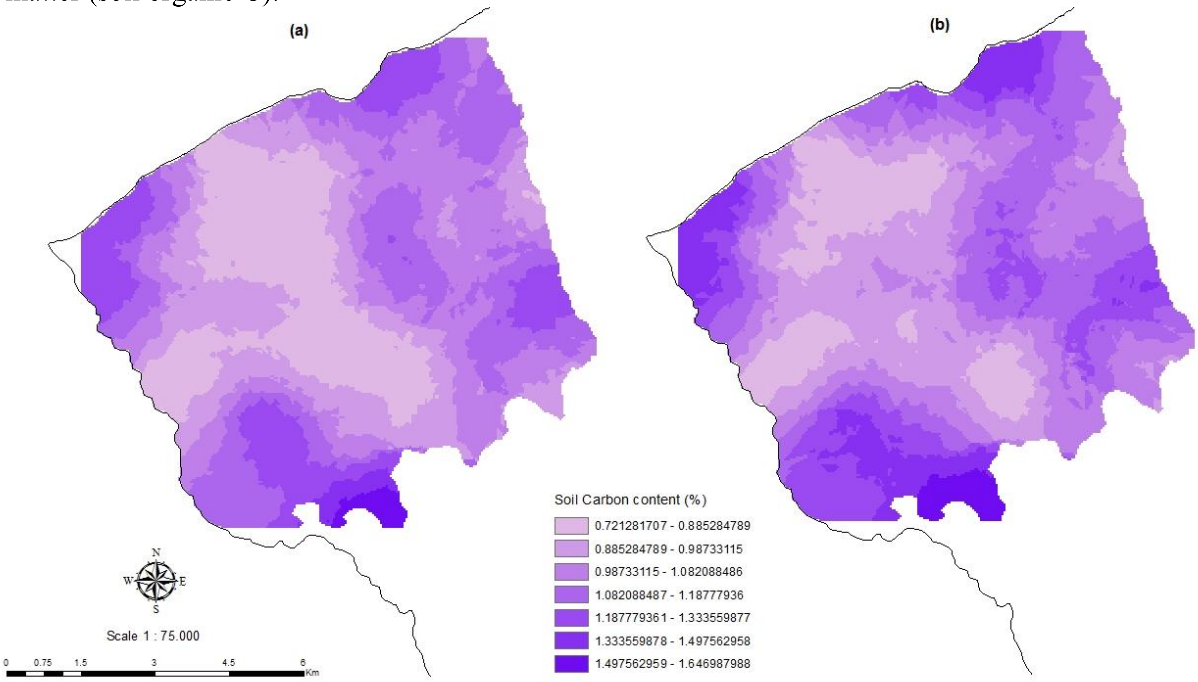

Figure 4. Distribution of soil C content in the study area: (a) measured by conventional analysis and (b) predicted by near-infrared technology.

With the average of soil bulk density 1.00 g cm^{-3} and the average of soil C content of laboratory analysis (Walkley and Black) and NIRS 1.03% C, thus the soil C stock per ha of 10 cm soil depth is 10,300 kg. As NIRS technique produced similar soil C stock (10,300 kg/ha/10 cm soil depth) to the laboratory analysis, so this technique may be used as a rapid measurement of soil C stock.

4. Conclusion

The near-infrared technology was able to be used for a rapid measurement and mapping of soil C stock in Kayangan agricultural area, North Lombok, Indonesia. The ability of this rapid technique to measure and map soil C content can give benefit for monitoring C stock in the soil, which in turn it may be used to monitor soil C (as CO_2) emitted to the atmosphere or sequestered to the soil. Then the information may be used to study the potential risk of global warming caused by depletion of soil C stock. This technique may also be employed to warn the critical level of C stock that may cause soil fertility and environmental problem.

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