POTENTIAL OF VISIBLE AND NEAR INFRARED SPECTROSCOPY FOR PREDICTION OF PADDY SOIL PHYSICAL PROPERTIES

A. Gholizadeh, M.S.M. Amin, and M.M. Saberioon

Center of Excellence of Precision Farming
Faculty of Engineering
University Putra Malaysia
Serdang, Selangor, Malaysia

ABSTRACT

A fast and convenient soil analytical technique is needed for soil quality assessment and precision soil management. The main objective of this study was to evaluate the ability of Visible (Vis) and Near-infrared Reflectance Spectroscopy (NIRS) to predict paddy soil physical properties in a typical Malaysian paddy field. To assess the utility of spectroscopy for soil physical characteristics prediction, we used 118 soil samples for laboratory analysis and optical measurement in the Vis-NIR region using ASD FieldSpec spectroradiometer (350-2500 nm). Savitzky-Golay algorithm and Stepwise Multiple Linear Regression (SMLR) were then applied to preprocess, model and predict the properties on the basis of its spectral reflectance within the Vis-NIR range. One-third of the total samples (40 samples) from different places were withheld for validation purpose. The study revealed that the Vis and NIR spectroscopy calibration models for all the measured soil physical characteristics indicated that Vis and NIR (specifically NIR reflectance) can be considered as a good tool to assess soil physical characteristics in Malaysian paddy fields. NIRS also has the potential of the modelling and prediction of soil information. The results of this study could be a significant contribution to develop the site-specific management decision and sustainable agriculture.

Keywords: Paddy field, Near infrared, Spectroradiometer, Site-specific management

INTRODUCTION

Managing our base resources wisely has become more important now than ever before since the gaining of larger amounts of accurate soil data is necessary so as to meet the food and fiber demands of future populations (Viscarra Rossel and McBratney, 1998). It is perhaps for these reasons that spectroscopic techniques, such as Vis and spectroscopy, are considered as possible alternatives to improve or replace conventional laboratory methods of soil analysis (Janik et al., 1998). Most of these techniques are non-destructive and therefore allow the protection of the basic integrity of the soil system.

Portable NIR sensors have the potential to facilitate the intensive field sample analysis required by Precision Farming (PF). The reasons why NIRS is being adopted as a preferred analytical method include minimal sample preparation, non-destructive methods, fast simultaneous analysis of constituents, lower staff requirements, cost-effective analysis of a single or batch of samples, no hazardous chemicals are needed and results can be very accurate (Batten, 1998).

In soil science, NIR is recently used to assess clay content, specific surface area, Moisture Content (MC) and other soil properties (Velasquez et al., 2005). Other researchers extended the application of non-mobile Vis-NIR spectroscopy for the measurement of other soil physical and chemical properties (Shepherd and Walsh, 2002; Bogrecki and Lee, 2005; Cozzolino and Morón, 2006).

Meanwhile, 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 attributes. For example, Shibusawa et al. (2001) used SMLR for the estimation of various soil properties from the NIR spectra of soil. Partial Least Squares (PLS) (Sørensen and Dalsgaard, 2005; Viscarra Rossel et al., 2006; Mouazen et al., 2007; Aichi et al., 2009) has also been used for spectral calibration and prediction. Although PLS is good for modeling spectral data, Bajwa et al. (2010) described that it is too complex for growers and crop consultants to adopt, compared to SMLR which is much simpler and more flexible.

The success of the spectral library approach is primarily dependent up on its ability to recommend models for the prediction of soil properties from soil reflectance spectra. Thus, to test the overall library approach for developing prediction models of some paddy soil, using important characteristics based on reflectance simply by means of a spectrometer operating between 350 and 2500 nm seems to be a helpful and immediate method.

MATERIALS AND METHODS

Study area

This study was conducted at Tanjung Karang rice irrigation scheme. The scheme area is located on a flat coastal plain in the Northwest Selangor integrated agricultural development project (IADA). It is in the district of Kuala Selangor and Sabak Bernam on latitude 3˚ 35" N and longitude 101˚ 05" E, covering an area of about 20,000 ha extending over a length of 40 km along the coast with a width of 5 km on average. The main irrigation and drainage canals run parallel to the coast. The scheme is composed of eight compartments; one of them is named as Sawah Sempadan with a total area of

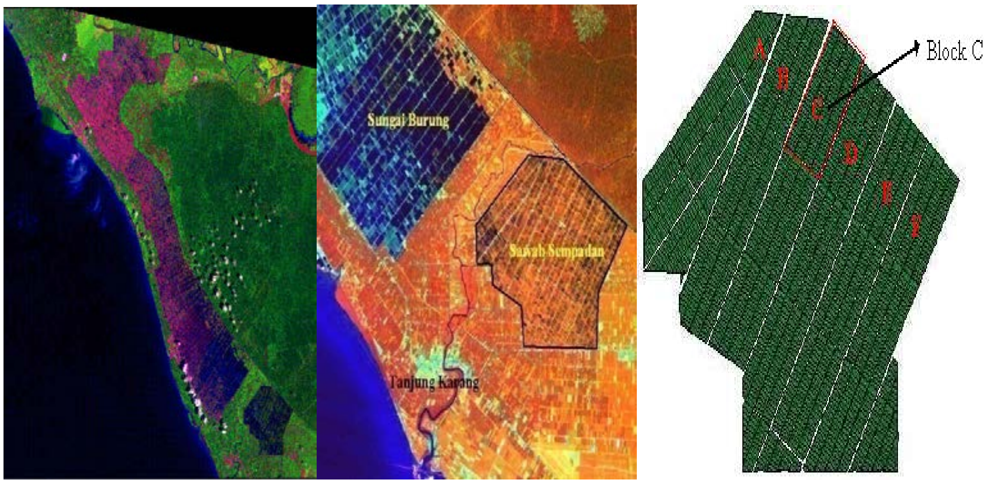


Fig. 1. The study area location at Sawah Sempadan rice irrigation compartment and Block C.

2300 ha. This compartment is divided into 24 blocks, i.e. blocks A to X. Block C is the chosen study area that contains 118 lots and each lot size is 1.2 ha with a total area of about 142 ha. It is located at the upstream of the irrigation scheme canal adjacent to the Tanjung Karang swamp forest. Figure 1 shows a map of the area.

Soil and spectral reflectance data collection

118 soil samples were collected within the root zone depth. The samples were then divided into two parts, whereby one part was for the optical measurements. Samples for laboratory analysis were brought to the soil laboratory for physical (Db, MC, Clay, Silt and Sand) analyses and the samples for optical measurement purpose were stored in plastic bags at 4°C, i.e. from the time of sampling until the time of analysis (Mouazen et al., 2007). The spectral reflectance of soil samples was measured in the Vis-NIR region using ASD Fieldspec spectroradiometer, which is a field portable and precision instrument with a spectral range of 350-2500 nm.

Pretreatment and calibration of spectral data

The SMLR technique was used to calibrate the spectral data using the laboratory soil data. The data were treated with SAS 9.2 and Unscrambler 10.0.1. Many resources like interfering physical and/or chemical factors, imperfections in the experimental apparatus and/or other random factors may cause NIR spectral noises (Xu et al., 2008). Some other unwanted parameters plaguing NIR spectra are complex backgrounds and baselines cause non-concentration-correlated contributions to the spectral data. These spectral variations would bring an unreasonably complicated and low accuracy calibration model (Spiegelman et al., 1998). Thus, it is necessary to preprocess NIR spectra properly to remove of noises, backgrounds and baselines. So, the first step in developing the calibration models is the pretreatment of the spectral data. Several pretreatments were considered and the best performing pretreatment was the second derivative of Savitzky-Golay method with a nine point moving-average filter, second-degree polynomial (Savitzky and Golay, 1964; Mouazen et al., 2007). The selection criteria of any pretreatment were the largest coefficient of multiple determinations (R^2) and the smallest Root Mean Square Error (RMSE) (Mouazen et al., 2007; Aichi et al., 2009).

The calibration models for the studied properties were established based on finding the relationships between the pretreated spectra and the laboratory reference measurement of the soil properties (Mouazen et al., 2007). The resulting calibration model can be used to estimate the modelled property in the new samples with the properties falling within the property of the calibration set.

RESULTS AND DISCUSSION

Vis-NIR reflectance spectroscopy of the soil samples and data pretreatment

All the soils tested in this study had similar reflectance spectra, with minor features apparent in the Vis and NIR portions of the spectrum (Fig. 2). Greater numbers of reflectance peaks were apparent in the NIR region as they had three major reflectance peaks (around 1150, 1650, and 2200 nm) that were analogous which those by Chang et al. (2001) and Haiyan et al. (2005).

Some frequently used pretreatment methods such as Multiplicative Scatter Correction (MSC), Standard Normal Variate (SNV) and Savitzky-Golay were carried out to determine the best data pretreatment algorithm, and finally, Savitzky-Golay was chosen as a proper data pretreatment method (Savitzky and Golay, 1964; Mouazen et al., 2007) because of the larger R^2 and smaller RMSE. Figure 3 describes the results of the Savitzky-Golay method obtained in pretreatment step.

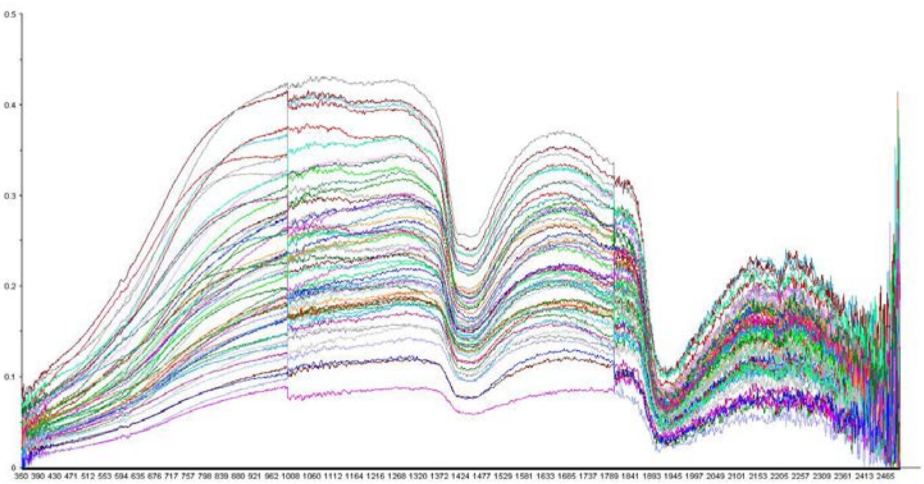


Fig. 2. Soil samples reflectance spectra.

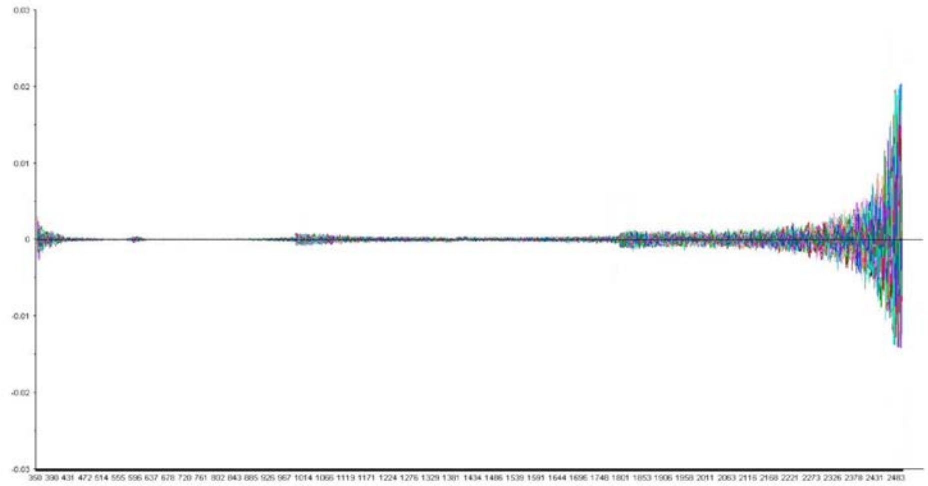


Fig. 3. Pretreatment by Savitzky-Golay method.

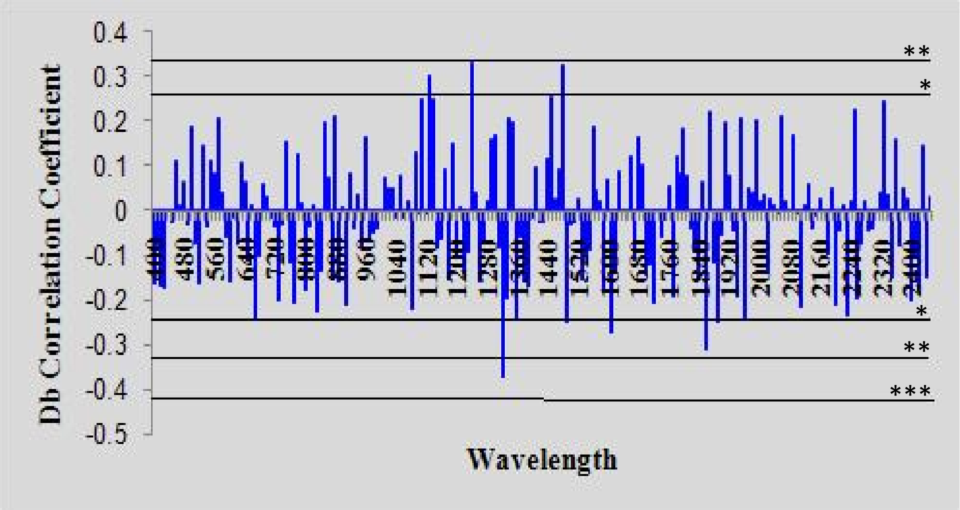
Matrix correlation of soil properties and reflectance spectra

Matrix correlations were carried out to check whether a different spectroradiometer wavelength has correlation with each soil property (Fig. 4 to Fig. 8). Attention to the spectra from Vis and NIR spectroscopy for a typical Malaysian paddy soil showed obvious differences in the correlation of spectral data in the Vis and NIR regions with the soil parameters. A comparison of Vis and NIR spectroscopy correlation to soil physical properties indicated that the NIRS performed significantly better correlation than those of the Vis spectroscopy.

The study concluded that all the selected soil physical properties (Db, MC, clay, silt and sand) provided a good significant correlation values at the NIR region. It also demonstrated how qualitative soil interpretations could aid with the identification and assignment of specific spectral bands to soil parameters.

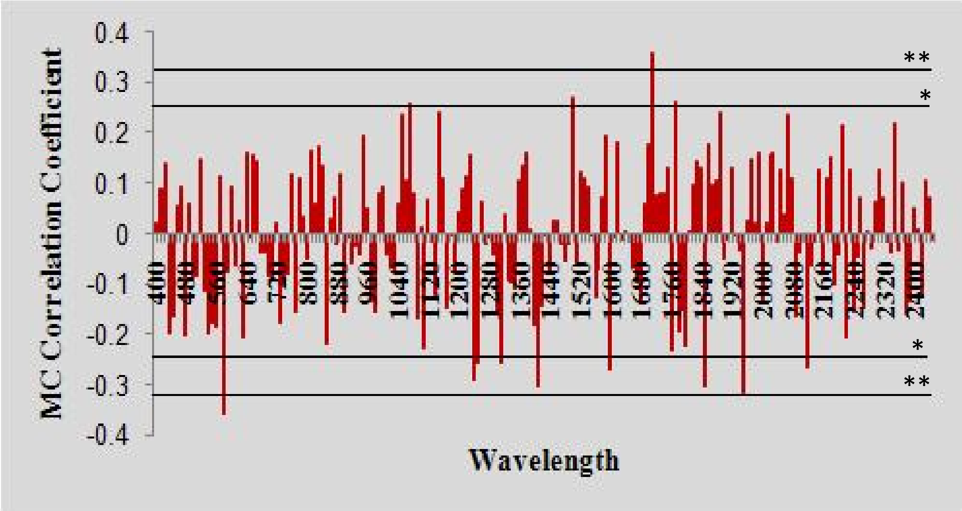
Some NIR wavelengths had better coefficients related to different components; for instance in the MC and sand correlation peak can be seen in λ= 1940 nm and λ= 1320 nm respectively, which are significant positive correlation. In spite of the parameters mentioned above, Db, clay and silt were negatively correlated to NIR reflectance at specific wavelengths of λ= 1320 nm, λ= 2210 nm and λ= 1320 nm correspondingly.

The reason that most of the parameters were correlated to NIR could probably because the NIR spectra were more influenced by the structure of the materials. The significant correlation of soil properties with the spectrum Vis and NIR regions having similar results has also been documented by several other researchers such as Al-Abbas et al. (1972), Krisnan et al. (1980), Morra et al. (1991), Haiyan et al. (2005).



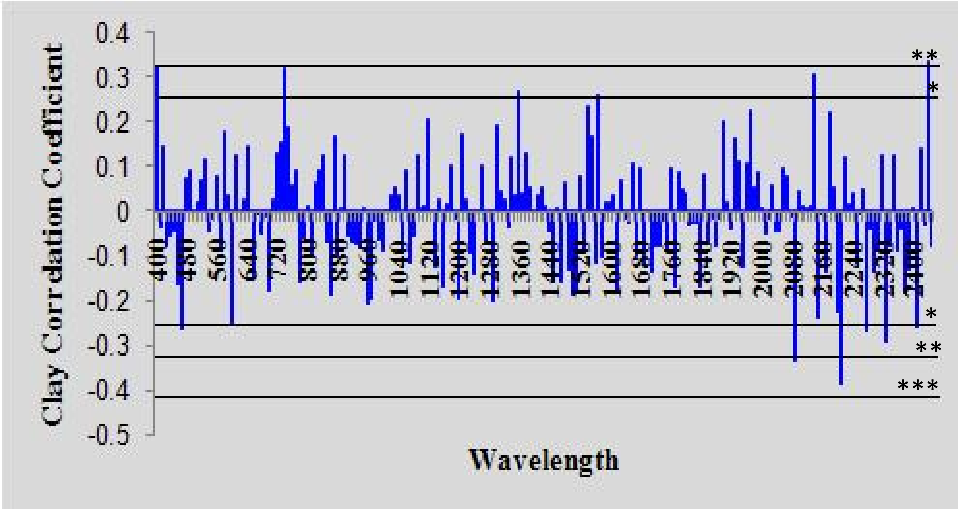
*** Correlation is significant at the 0.001 level (2-tailed).
** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

Fig. 4. Pearson matrix correlation coefficient of wavelength and Db.



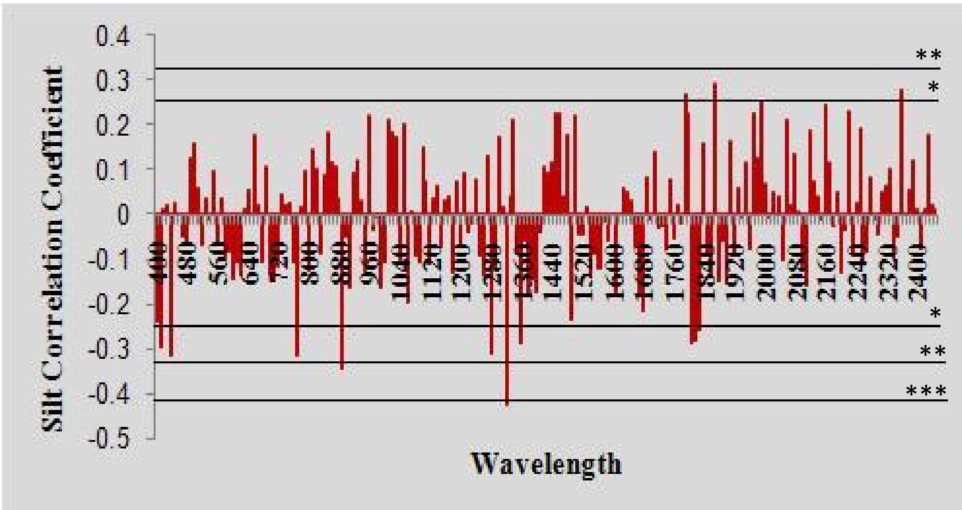
** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

Fig. 5. Pearson matrix correlation coefficient of wavelength and MC.



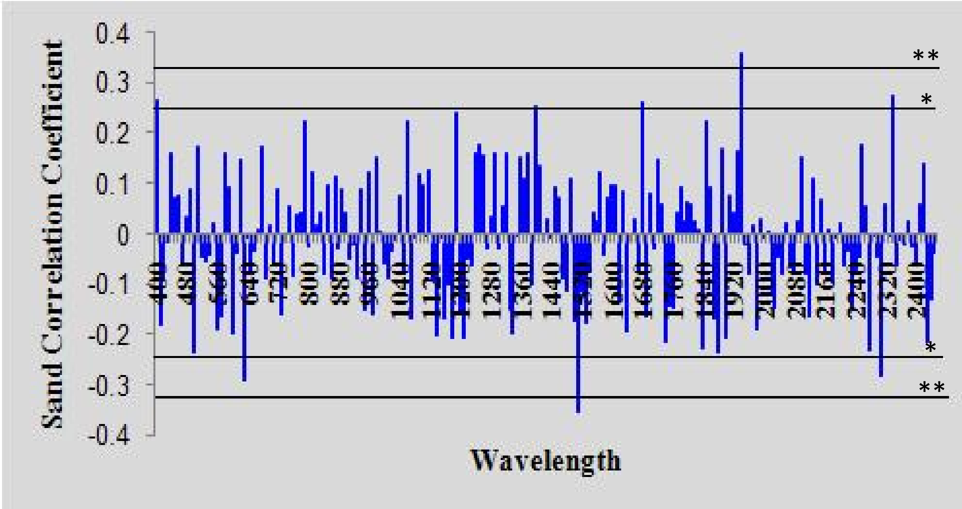
*** Correlation is significant at the 0.001 level (2-tailed).
** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

Fig. 6. Pearson matrix correlation coefficient of wavelength and clay.



*** Correlation is significant at the 0.001 level (2-tailed).
** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

Fig. 7. Pearson matrix correlation coefficient of wavelength and silt.



** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

Fig. 8. Pearson matrix correlation coefficient of wavelength and sand.

Development of prediction models

In the Vis-NIR spectroscopy, the average R^2 value for the prediction of soil Db, MC, clay, silt and sand amount were 0.99, 0.82, 0.99, 0.97 and 0.96 respectively (Fig. 9 to Fig. 13), suggesting that the general calibration model for soil physical properties, might be useful to predict this parameter in the paddy soils in Malaysia. These figures also indicate the effects of 41, 20, 34, 33 and 29 wavelengths in the prediction model of abovementioned soil physical properties.

Sudduth and Hummel (1993), Chang et al. (2001), Slaughter et al. (2001) and Mouazen et al. (2007) also evaluated and determined the prediction of MC with Vis-NIRS as good. The results obtained by Shepherd and Walsh (2002) as well as Sørensen and Dalsgaard (2005) have also demonstrated that the NIR spectroscopy is a potential technique for rapid and cost effective determination of clay in soils. On the contrary, Viscarra Rossel et al. (2006) suggested that the precision of the MIR technique for soil clay prediction is more accurate than NIR. Chang et al. (2001) have also reported that silt was successfully predicted by NIRS. And finally, the results of this study about sand amount are similar to those by Chang et al. (2001).

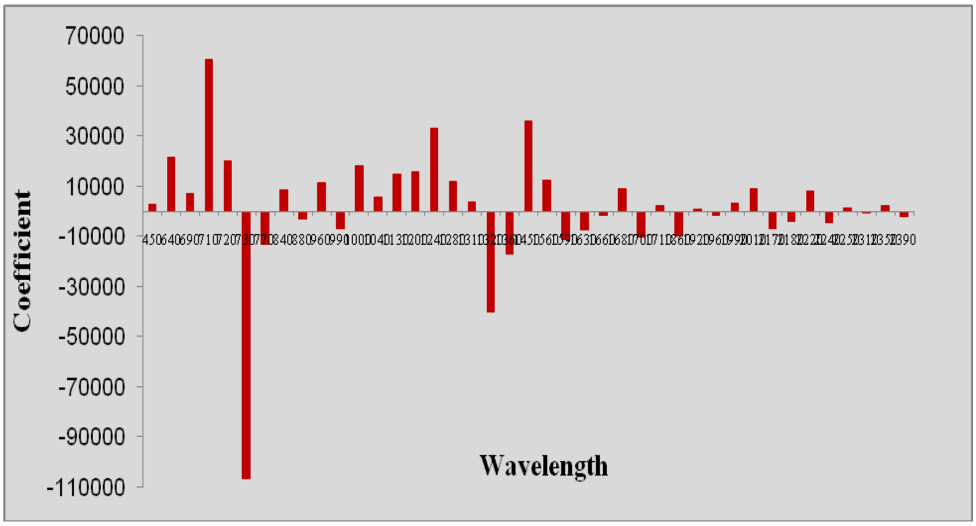


Fig. 9. Prediction coefficient of soil Db based on reflectance for each selected wavelength after SMLR.

Db= 22.40168 + 2712.262 λ_{450} + 21319 λ_{640}+ … – 2058.15 λ_{2390}
λ_n= 41
R^2= 0.99

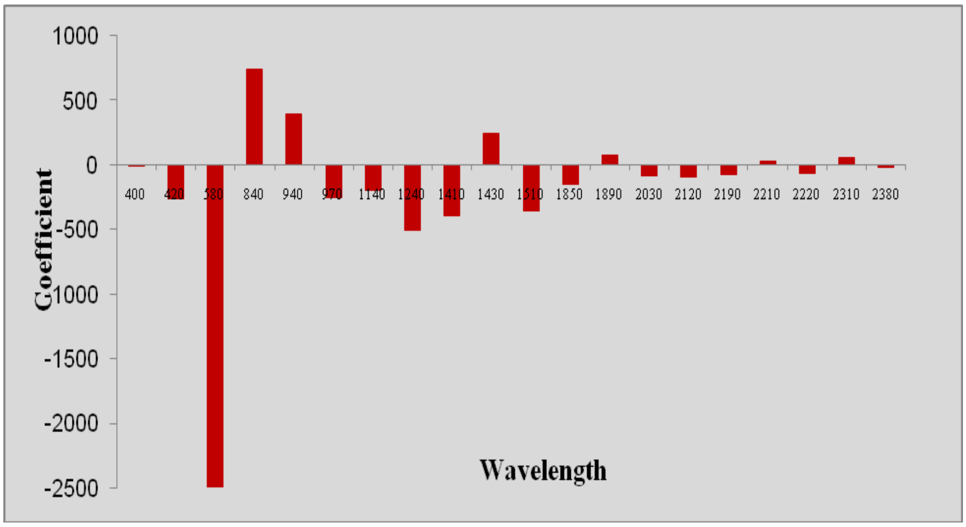


Fig. 10. Prediction coefficient of soil MC based on reflectance for each selected wavelength after SMLR.

MC= 1.14526 - 0.0008 λ_{400} – 266.931 λ_{420}+ … – 19.5818 λ_{2300}
λ_n= 20
R^2= 0.82

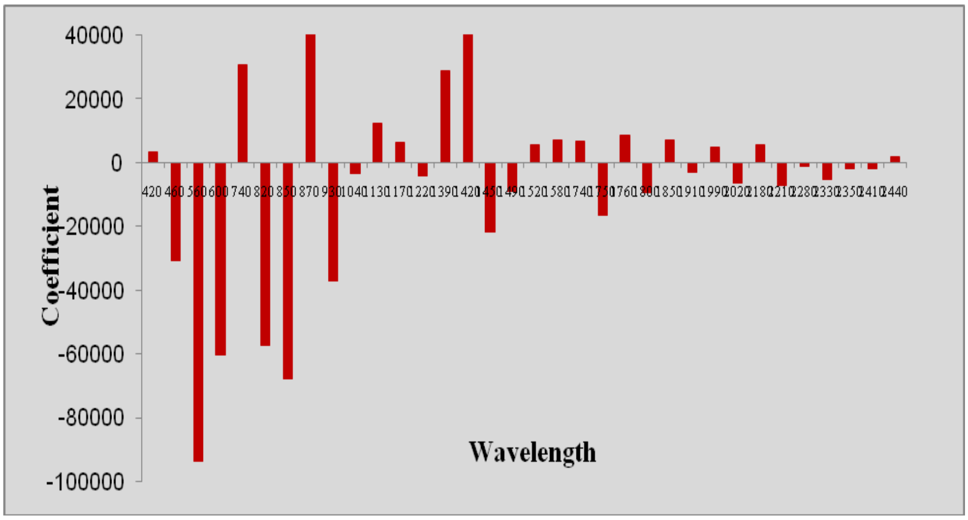


Fig. 11. Prediction coefficient of soil clay based on reflectance for each selected wavelength after SMLR.

Clay= 51.59423 + 3268.53 λ_{420} – 30901 λ_{460}+ …+ 1907.649 λ_{2440}
λ_n= 34
R^2= 0.99

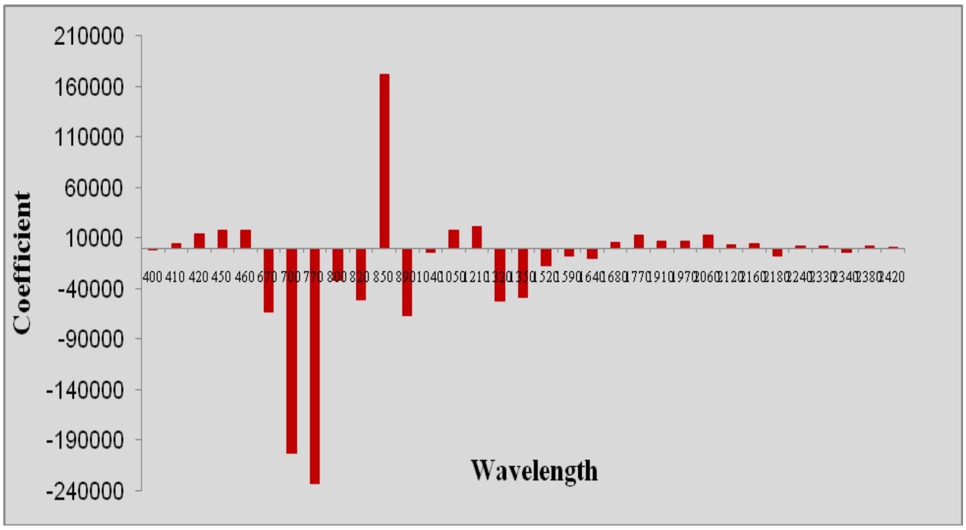


Fig. 12. Prediction coefficient of soil silt based on reflectance for each selected wavelength after SMLR.

Silt= 40.32787 – 0.13093 λ_{400} + 4312.756 λ_{410}+ … – 1158.431 λ_{2420}
λ_n= 33
R^2= 0.97

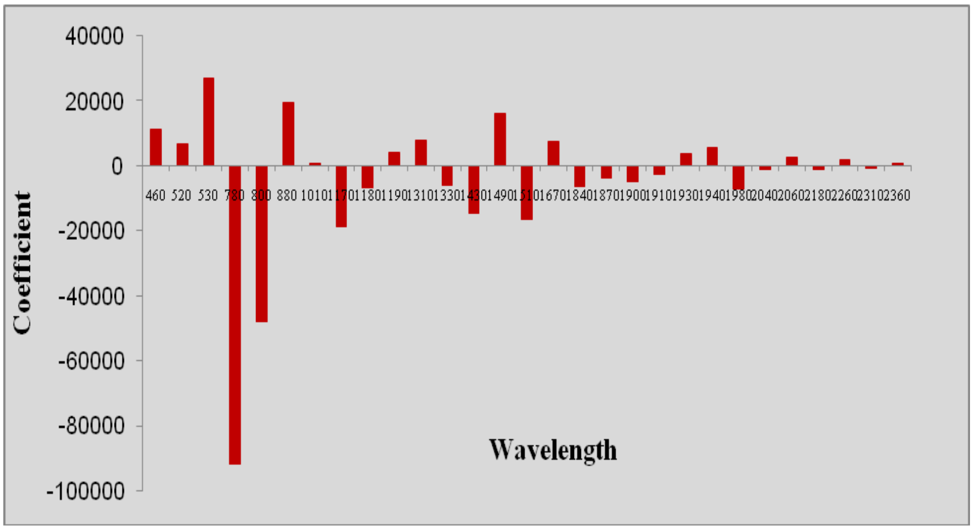


Fig. 13. Prediction coefficient of soil sand based on reflectance for each selected wavelength after SMLR.

Sand= 46.06134 + 11246 λ_{460} + 6572.966 λ_{520}+ …+ 676.4661 λ_{2360}
λ_n= 29
R^2= 0.96

Validation test

Validation is a quality control process that is used to evaluate whether or not a product or system complies with the regulations, specifications or conditions imposed at the start of a development phase. For this reason in this study, carrying out a validation test using one-third of the total number of the samples taken from different places was due to the environmental change which showed that the validation set had predicted well by the calibration set.

Same as the Vis and NIR spectroscopy correlation to the soil physical properties in calibration, in the validation test, all measured parameters performed significantly better correlation to NIR range too. Meanwhile, specific wavelength showing the highest correlation to each soil parameter can be seen in Table 1.

Table 1. Summary of specific wavelength correlation to soil parameters and yield.

Soil Properties	Wavelength (nm)	Correlation Type
Db	1370	Negative
MC	1540	Positive
Clay	2040	Negative
Silt	1380	Negative
Sand	1940	Positive
Yield	1380	Positive

In the validation test, the correlation coefficient across the entire spectral region between 400-2450 nm for each component during both the calibration and validation indicated that the wavelengths possessed better coefficients related to the soil physical properties all belonging to the NIR region of the spectrum.

The ability of the NIRS to predict the physical properties of soil in Malaysian paddy fields was also validated and its ability for these purposes has been confirmed. Meanwhile, the adequacy of each model and prediction ability was evaluated based on the values of R^2 in both calibration and validation (Table 2). It is clear that the R^2 values are sufficient indicator for using NIRS as a prediction technique in a typical Malaysian paddy field.

Table 2. Calibration and validation R^2 values for soil properties prediction.

Soil Properties	R^2 (Calibration)	R^2 (Validation)
Db	0.99	0.98
MC	0.82	0.93
Clay	0.99	0.98
Silt	0.97	0.97
Sand	0.96	0.96

CONCLUSION

This study has described a conceptual frame work for using of Vis-NIR spectroscopy in Malaysian paddy fields which is based on the reflectance spectra of the soil; it is rapid, non-destructive, straightforward model, which is sometimes more accurate than the conventional analysis of soil physical properties. All the soils tested in this study were shown to have similar reflectance spectra and greater numbers of reflectance peaks in the NIR region especially around λ= 1150, λ= 1650 and 2200 nm). A comparison of the Vis and NIR spectroscopy correlation with the soil physical properties indicated that the NIRS performed significantly better correlation than those of the Vis spectroscopy. In addition, the NIRS calibration models for all the soil parameters which had been developed in this study provided a good fit (R^2 > 0.80), which demonstrating the potential of diffuse reflectance spectroscopy using Vis and especially the NIR for more efficient soil analysis, as well as the modeling and prediction of soil information. From the results of this investigation, the NIRS-SMLR is a technique that can be considered to have a good potential in assessing the physical (Db, MC, clay, silt, sand) properties of the soil in paddy fields in Malaysia. Moreover, NIRS could be useful *in situ* as a rapid technique that can be combined with the GIS and application of the PF principles. Hence, the results of the experiments could be a significant contribution to develop the site-specific management decision and sustainable agriculture.

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