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In situ near-infrared spectroscopy for soil organic matter prediction in paddy soil, Pasak watershed, Thailand

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ABSTRACT

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Soil organic matter (SOM) is a major index of soil quality assessment because it is one of the key soil properties controlling nutrient budgets in agricultural production systems. The aim of the *in situ* near-infrared spectroscopy (NIRS) for SOM prediction in paddy area is evaluation of the potential of SOM and prediction of other soil properties. There are keys for soil fertility and soil quality assessments. A spectral reflectance of 130 soil samples was collected by field spectroradiometer in a region of near-infrared. Spectral reflectance collections were processed by the first derivative transformation with the Savitsky-Golay algorithms. Partial least square regression method was used to develop a calibration model between soil properties and spectral reflectance, which was used for prediction and validation processes. Finally, the results of this study demonstrate that NIRS is an effective method that can be used to predict SOM (R^2 = 0.73, RPD (ratio of performance to deviation) = 1.82) and total nitrogen (R^2 = 0.72, RPD = 1.78). Therefore, NIRS is a potential tool for soil properties predictions. The use of these techniques will facilitate the implementation of soil management with a decreasing cost and time of soil study in a large scale. However, further works are necessary to develop more accurate soil properties prediction and to apply this method to other areas.

Keywords: remote sensing; non-destructive technique; land use; soil spectral reflectance; nutrient

A measurement of soil organic matter (SOM) is important because it is a key component in the creation and maintenance of a high quality soil. It affects, directly or indirectly, many physical, chemical and biological properties that control soil productivity and resistance to degradation (Dick and Gregorich 2004). Various types of human activities, particularly agricultural use, decrease SOM contents as well as soil biological activities (FAO 2005). A determination of soil quality can be derived from some soil properties. Indicators of soil quality will reflect important soil functions (Magdoff and Weil 2004).

Remote sensing has the capability of synoptic view, large area repeat coverage and continuous spatial dataset, whereas GIS (geographic information system) integrates spatially referenced datasets for purposes of modelling and informative decision-making (Ben-Dor et al. 2009). Near infrared spectroscopy (NIRS) is a very fast non-destructive and environmentally friendly analytical technique (Zbíral et al. 2017). NIRS analysis enables the evaluation of soil characteristics related to SOM including soil moisture (SM), total nitrogen (TN), cation exchange capacity (CEC), available phosphorus (avail. P), clay and calcium carbonate ($CaCO_3$) (Velesquez et al. 2005). Thus,

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NIRS is an effective tool for studying soil properties in large spatial domains.

This study was realized because a population growth requires an increase of natural and environmental resources and a land use change by human driving force causes a problem to soil quality. Pasak watershed is one of the important agricultural areas of Thailand. Rice, corn, tobacco and vegetables are common agricultural products of the Pasak watershed. The aim of this study was (i) to predict SOM and other soil properties by the NIRS method in paddy soil and (ii) to evaluate a potential of the NIRS predicted soil properties.

MATERIAL AND METHODS

Study area and soil samplings. The study area is a part of the Pasak Section-2 sub-watershed that is located in the north of the Pasak watershed in the Petchabun Province, Thailand (101°14'3.21''E, 16°37'0.22''N) (Figure 1). Study area is a valley landscape and the soils were classified as moderately developed Inceptisols, namely Lom Sak series (fine-silty, mixed, superactive, non-acid, isohyperthermic Fluvaquentic Endoaquepts). 130 soil samples were collected from 0–20 cm topsoil. Area selection was considered from a prepared area for planting rice or corn in paddy field area. Sampling sites were generally after tillage and residues such as straw rice and corncobs on surface were found in several sites.

Soil properties analysis. Soil samples were air-dried, gently crushed and then passed through a 2 mm stainless steel sieve. The resultant < 2 mm samples were used for laboratory analysis. Soil organic carbon (SOC) was determined by the Walkley-Black method (Nelson and Sommers 1996). TN was determined by the Micro Kjeldahl method (National Soil Survey Center 1996). pH was measured with a pH electrode in 1:1 suspensions (soil:H_2O). Avail. P was determined by the Bray II method (Bray and Kurtz 1945). Available potassium (avail. K) was determined by 1 mol/L NH_4OAc at pH 7.0 extraction and measured by the atomic absorption spectrometric (AAS) (Pratt 1987). CEC and the percent base saturation (%BS) were measured by the ammonium saturation method at pH 7.0 (National Soil Survey Center 1996).

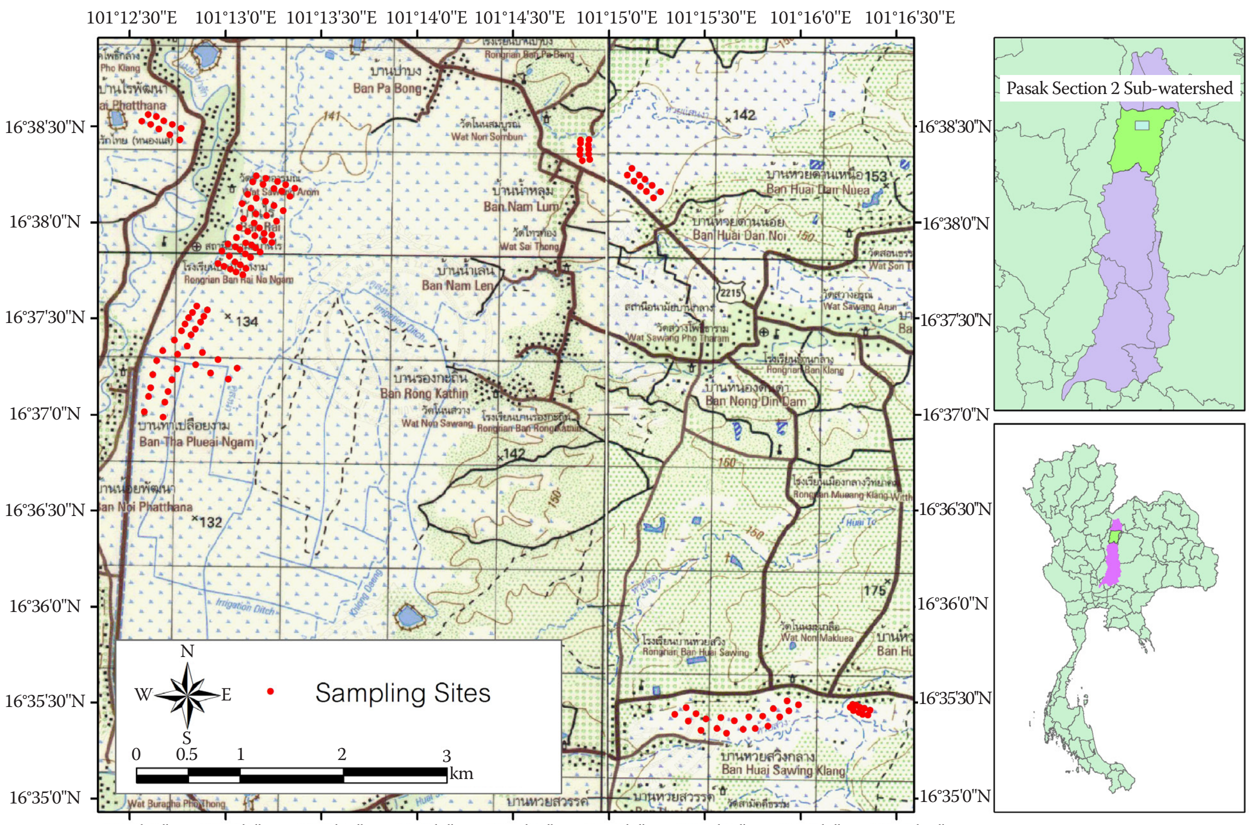

Figure 1. A study area in paddy field at the Pasak Section-2 sub-watershed, Petchabun Province, Thailand

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Table 1. Chemical soil properties of 102 soil samples used for calibration

Soil property	SOM	TN	pH	Avail. P	Avail. K	CEC	BS
	(g/kg)			(mg/kg)		($cmol_+$/kg)	(%)
Mean	28.64	1.4	6.03	19.11	118.27	25.27	74.14
Median	26.51	1.31	5.96	9.54	110.78	25.9	75.07
Max	69.02	3.24	7.72	178.4	572.29	53.9	103.31
Min	9.88	0.55	4.84	0.72	15.96	6.92	27.96
Standard deviation	14.16	0.65	0.68	32.54	84.58	8.28	12.48

SOM – soil organic matter; TN – total nitrogen; avail. P and K – available phosphorus and potassium; CEC – cation exchange capacity; BS – base saturation

NIRS pre-treatment and calibration. A field spectral reflectance of 130 soil samples was collected by using a handheld ASD FieldSpec 3 ASD spectroradiometer (ASD 1995). Spectral reflectance measured at a wavelength of 350–2500 nm was recorded for 30 replicates per sample. The spectral reflectance in the range of 350–2500 nm was used to correlate with soil properties. An undesired effects or noises of 130 soil spectral reflectance were removed from the data matrix. The head and the tail (350 to 400 nm and 2450 to 2500 nm) of spectral regions showed high noise and some spectral length regions were associated with water absorption in a length of 1351–1454, 1791–1969 and 2301–2500 nm that were removed from the data matrix. Three excluded regions of the wavelength were relative with other studies (Palacios-Orueta and Ustin 1996, Price 1998, He et al. 2009). The remaining spectral data were calculated to reduce the effect of multiple scattering of radiations using the first derivative transformation with the Savitsky-Golay algorithms with a window size of 11 and polynomial of order 2 (Savitsky and Golay 1964) to reduce the baseline variations and to highlight the peaks of spectral reflectance. All procedures were processed by the Unscrambler 10.4 software (CAMO, Inc., Oslo, Norway).

NIRS analysis and soil properties prediction. In total, 130 soil samples were divided into 2 groups; in group I, 102 samples were used to develop a calibration model with spectral reflectance and in group II, 28 samples were used to predict soil properties. Partial least square regression (PLSR) was one of the most common chemometrics in the NIRS analysis (McCarty et al. 2002, Zornoza et al. 2008, Feyziyev et al. 2016). PLSR was used to create calibration models relating spectral reflectance and soil properties. The best calibration predicted model was considered from the highest R^2 and the ratio of performance to deviation (RPD), the lowest of root mean square error (RMSE) of calibration. Predicted results of RPD were divided into three classes with (i) good prediction as RPD > 2; (ii) prediction with potential as RPD around 1.4–2 and (iii) unreliable prediction as RPD < 1.4 (Chang et al. 2001).

Table 2. Samples of soil fertility parameters rate agreement with the total score of soil fertility rate assessment, according to the standard criteria used in Thailand

Score rate	SOM[1]	Avail. P[1]	Avail. K[1]	CEC[1]	BS[1]	Soil fertility rate[2]
High	12	14	31	29	26	31
Moderate	51	25	18	12	39	65
Low	6	5	4	4	1	6
Total	69	44	53	45	66	102

[1]Standards: SOM (soil organic matter, g/kg): 15 > low (1), 15–35 – moderate (2), 35 < high (3); avail. P (mg/kg): 10 > low (1), 10–25 – moderate (2), 25 < high (3); avail. K (mg/kg): 60 > low (1), 60–90 – moderate (2), 90 < high (3); CEC (cation exchange capacity): 10 > low (1), 10–20 – moderate (2), 20 < high (3); and BS (base saturation, %): 35 > low (1), 35–75 – moderate (2), 75 < high (3). [2]Soil fertility rates: total score 7 > low, 8–12 – moderate, 13 < high. Source: Soil Survey Division (1980)

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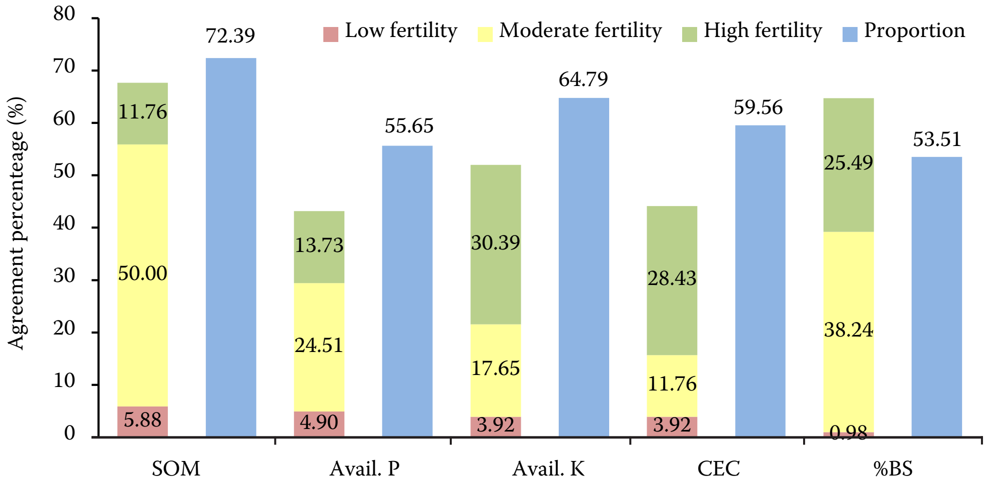

Figure 2. Proportional agreements between the rate of soil parameters and total score of soil fertility assessment. SOM – soil organic matter; avail. P and K – available phosphorus and potassium; CEC – cation exchange capacity; BS – base saturation

RESULTS AND DISCUSSION

Soil properties. The summary statistics of the measured soil properties from the laboratory analysis are shown in Table 1. Soil fertility assessment method was used to evaluate the soil fertility rate and to describe the characteristics of soil use in this area. The majority of soil properties (SOM, avail. P, avail. K, CEC and %BS) of 102 soil samples were used for soil fertility assessment (Table 2). The

Table 3. A comparison of validation results between this study and other study

Soil property	This study			Other study				
	R^2	RMSE	RPD	R^2	RMSE	RPD	study area/type of area	Reference
SOM	0.73	0.41	1.82	0.81	0.36	–	Malaysia/paddy field	Gholizadech et al. (2013)
				0.75	7.66	–	China/paddy field	Wenjun et al. (2014)
				0.98	6.25	5.75	Spain/Mediterranean	Zornoza et al. (2008)
				0.79	–	2.11	Canada/wheat	Martin et al. (2002)
				0.83	–	–	Azerbaijan/arid climate	Feyziyev et al. (2016)
TN	0.72	0.2	1.82	0.79	3.76	–	Malaysia/paddy field	Gholizadech et al. (2013)
				0.86	0.03	–	China/paddy field	Wenjun et al. (2014)
				0.95	0.41	4.69	Spain/Mediterranean	Zornoza et al. (2008)
				0.30	–	1.14	Canada/wheat	Martin et al. (2002)
				0.44	–	–	Azerbaijan/arid climate	Feyziyev et al. (2016)
pH	0.21	0.56	1.06	0.72	0.14	1.90	Spain/Mediterranean	Zornoza et al. (2008)
				0.65	–	–	Azerbaijan/arid climate	Feyziyev et al. (2016)
Avail. P	0	16.75	0.9	0.46	2.02	1.36	Spain/Mediterranean	Zornoza et al. (2008)
				0.73	–	–	Azerbaijan/arid climate	Feyziyev et al. (2016)
Avail. K	0.29	52.82	1.15	0.79	0.11	2.19	Spain/Mediterranean	Zornoza et al. (2008)
CEC	0.2	4.11	1.08	0.92	0.06	3.46	Spain/Mediterranean	Zornoza et al. (2008)
				0.83	–	–	Azerbaijan/arid climate	Feyziyev et al. (2016)

SOM – soil organic matter; TN – total nitrogen; avail. P and K – available phosphorus and potassium; CEC – cation exchange capacity; RMSE – root mean square error; RPD – ratio of performance to deviation

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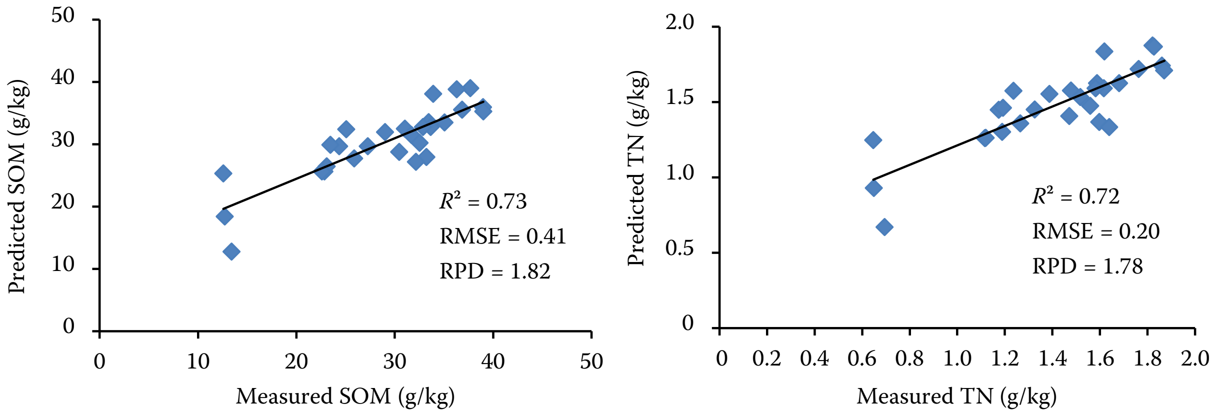

Figure 3. A validation of soil organic matter (SOM) and total nitrogen (TN) prediction between the measured and predicted data. RMSE – root mean square error; RPD – ratio of performance to deviation

results of soil fertility assessment show that there were 31 high fertility samples, 65 moderate fertility samples and 6 low fertility samples included. From the results, it could be indicated that some soil properties parameters had a major impact to soil fertility total score. The study found that the rate of the SOM fertility agreed with the total score of the soil fertility assessment (72.39%) more than other soil property parameters (Figure 2). It could be concluded that SOM had ability to impact soil fertility or soil quality in the study area. Thus, a predicted SOM could be elementary information for soil resources and land use management.

NIRS and soil properties prediction. All calibration and validation statistics were shown in Table 3. A validation result of predicted soil properties had a strong correlation between soil spectral reflectance and most of the soil properties included SOM (0.73, 0.41, 1.82), TN (0.72, 0.20, 1.78), had a high R^2, low RMSE and potential prediction as RPD (Figure 3). The study result showed that soil properties including SOM and TN had a good potential prediction. Similar results to those studied with SOM and TN were reported in other studies (Table 3). This study had similar results to other studies that had moderately high accuracy of the predicted results especially in paddy field area in a case study in Malaysia and China (Gholizadech et al. 2013, Wenjun et al. 2014). In addition, other land use types such as the Mediterranean regime with various land uses in Spain and a wheat crop land use in Canada both had high accuracy of SOM prediction, while the predicted TN result in wheat crop area had low accuracy (Martin et al. 2002, Zornoza et al. 2008).

Chang and Laird (2002) reported that TN prediction was identified by SOC prediction. However, NIRS calibrations for TN rarely perform better than the corresponding calibration for SOM (Rossel et al. 2006). This was reliable because NIRS provided information about relative proportions of bonds such as C-H, N-H, S-H and O-H, present in the organic compounds (O-H also included in the water molecule). Rossel and Behrens (2010) found that SOC was related to wavelengths that represent absorptions due to organic molecules and proteins with C-O and N-H bonds. The other predicted soil properties such as pH, avail. P, avail. K, CEC and %BS had poor result. However, these results were similar to those of another study with low accuracy of soil properties prediction with avail. P (Zornoza et al. 2008).

It is concluded that the potential of soil properties prediction using NIRS technique had a moderately high accuracy. Thus, NIRS is a reliable and effective measurement tool that could be used to predict soil properties, and particularly SOM that is the key to evaluate soil fertility or soil quality. It is important information and decision support for planning or managing agricultural area in a large scale. PLSR had ability to develop a calibration model relating soil properties and the pre-processed spectral reflectance. Therefore, it is possible to use the NIRS technique and PLSR analysis to evaluate SOM and TN. The use of these techniques will facilitate the implementation of soil management in a large scale. However, further works have to develop more accuracy of soil properties prediction and apply NIRS and PLSR techniques to predict other characteristics of land use or landscape in another area.

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