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Research article

The Potential of Near-infrared Spectroscopy to Predict Soil Nutrient Contents Based on Soil Color

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Abstract: Near-infrared spectroscopy (NIR) analysis in laboratory-based settings has the potential to predict soil elements. The aim was to explore the effects of soil color on the prediction of total nitrogen (N), available phosphorus (P), and extractable potassium (K) contents using near-infrared spectroscopy in the range of 1000–2500 nm. Two hundred forty soil samples were collected from a paddy field in northeast Thailand. We divided the soil samples based on soil color using the Munsell color chart to construct a model to predict nutrient contents based on soil color. Regression models for soil nutrient contents were developed using partial least squares regression (PLSR) models. The best predictions were obtained for N (R^2 = 0.87, RMSE = 0.131), P (R^2 = 0.87, RMSE = 7.713) and K (R^2 = 0.77, RMSE = 14.944). This research demonstrates the viability of employing Near-Infrared spectroscopy (NIRs) as a reasonable method for predicting soil nutrient contents.

Keywords: Soil color; Paddy soil; Soil nutrient contents; Near infrared; Partial square regression

1. Introduction

In recent years, there has been a significant demand for soil analysis methodologies that are precise, rapid, and pollution-free. This is because soil data information can be utilized for environmental monitoring, soil quality assessment, and precision agriculture [1, 2]. For this reason, near-infrared spectroscopy (NIRs) is considered an alternative to improve or complement traditional methods of soil analysis. Near-infrared spectroscopy has emerged over the past few decades as a rapid and robust analytical method for various agricultural applications [3]. In particular, this technique can assess various soil fertility properties simultaneously with a single spectrum, making reflectance infrared spectroscopy fast, time-saving, cost-effective, and efficient. In the NIR region, radiation is absorbed by different chemical bonds present in the sample, such as C–H, N–H, S–H, C=O, and O–H. Furthermore, the radiation is absorbed in a manner conforming with the concentration of these compounds. As a result, NIR reflectance spectra provide information about the organic composition of a soil sample. Nevertheless, NIR information cannot be directly inferred from the obtained spectra. NIR reflectance spectroscopy depends on calibrations and chemometrics techniques that employ absorbances at multiple wavelengths to predict particular characteristics of a sample [4]. Thus, research on using near-infrared (NIR) spectroscopy in soil science has rapidly increased to determine soil properties. Several authors have demonstrated the efficacy of NIR reflectance spectroscopy in predicting macro- and micronutrients in soils [2, 5–11].

Soil color is a crucial indicator of soil properties and processes that reflect chemical, physical, and biological characteristics [12–14]. The three principal constituents of soil color are humus (black), calcium carbonates (white), and iron oxide (red or yellow). However, other soil components, such as manganese oxides, nitrogen oxides, and phosphorus oxides, can also contribute to soil color. These important nutrients can be identified by color variables such as lightness [15–18]. Moreover, soil texture, organic matter content, moisture level, and erosion influence soil color [19–21]. Soil color is commonly evaluated by a human observer visually comparing the color of a soil sample to the color chips specified by the Munsell Color System [22]. The Munsell color chips are organized based on the hue, value, and chroma color components, and the method for measuring soil color is elaborated in detail in Soil Science Division Staff [23]. Previous studies have demonstrated strong relationships between soil properties and the spectral reflectance of soils in the visible and near-infrared regions [24–31]. Thus, the goal of this paper is to investigate the potential of near-infrared spectroscopy (NIRs) to predict total nitrogen (N), available phosphorus (P), and extractable potassium (K) in paddy soil, using soil color as a criterion to divide the soil samples into a calibration data set and a validation data set.

2. Materials and Methods

2.1 Study area, soil sampling collection, and chemical analyses

The soil sample in this study is paddy soil from northeast Thailand. It covers eight provinces, including Sakon Nakhon, Phanom, Amnat Charoen, Ubon Rachathani, Sisaket, Surin, Buriram, and Roi Et, with different soil groups. The samples were collected at depths of 0 –15 cm. In total, 240 samples were used for this experiment. The soil samples were air-dried and sieved using a 2-mm sieve. The laboratory chemicals were analyzed for the total nitrogen (N) content, which was determined by the Kjeldahl method [32]. The available phosphorus (P) content was determined by the Bray II method [33]. The method described by Jackson and Chen [32] measured the extractable potassium (K) content. Table 1. shows the summary statistics of the chemical analysis of soil N, P, and K.

Table 1. Descriptive statistics data of soil fertility used in this study.

Soil color group	Soil nutrients	Min	Max	Mean	SD
Group one (10YR Value 3-5)	N	0.21	1.40	0.68	0.37
	P	3.16	126.25	39.49	34.01
	K	0.04	442.25	71.37	64.14
Group two (10YR Value 6-7)	N	0.07	1.68	0.68	0.37
	P	1.42	80.68	17.81	13.77
	K	18.41	158.69	46.65	26.50
Group three (7.5YR Value 5-7)	N	0.07	6.30	0.68	0.94
	P	5.23	63.47	17.81	9.95
	K	15.51	175.31	53.25	38.45
Group four (5YR Value 6-7)	N	0.07	1.09	0.46	0.25
	P	1.66	106.95	15.57	21.12
	K	0.01	117.35	26.23	30.86

N = total nitrogen (g kg^{-1})
P = available phosphorus (mg kg^{-1})
K = extractable potassium (mg kg^{-1})

2.2 Spectrum determination and soil color

Spectral measurements in the 1000 – 2500 nm range were made with a Fourier-transform near-infrared (FT-NIR) spectrophotometer (Buchi N-500 NIRFlex; Switzerland). The measurements were conducted with a spectral resolution of 4 nm. The soil samples were placed in petri dishes and smoothed surfaces before the spectral measurement. We obtained the soil spectra in reflectance by averaging three scans for each sample. Subsequently, we converted the reflectance spectra to an absorbance spectrum (A) using $A = \log_{10}(1/R)$. Before modeling, we divided the soil samples based on the Munsell color chart to create a model that predicts nutrient contents depending on soil color. Color can be represented using three-dimensional color space models. Soil color is typically described in both dry and moist conditions using the Munsell color system, which is based on three parameters: hue (dominant spectral color), value (lightness), and chroma (color purity) [22]. For Munsell, soil color was determined in the laboratory for moist soil samples, and the Munsell soil color was chosen for the closest chip. As a result, we can divide soil color into four groups: group one, which has a hue of 10YR and a value of 3 to 5 (~10YR Value 3-5) totaling 60 samples; group two, which has a hue of 10YR and a value of 6 to 7 (~10YR Value 6-7) totaling 60 samples; group three, which has a hue of 7.5YR and a value of 5 to 7 (~7.5YR Value 5-7) totaling 60 samples; and group four, which has a hue of 5YR and a value of 6 to 7 (~5YR Value 6-7) totaling 60 samples.

2.3 Calibration Model

For model construction, we utilized Partial Least Squares regression (PLSR). PLSR is commonly employed as a chemometric technique in Near-Infrared (NIR) analysis [5, 35–37]. The PLS regression is a multivariate regression modeling method suggested by [38]. This method can be employed to address the issue of co-linearity among independent variables. The PLSR can effectively extract latent variables (LVs) by excluding unexplainable information, ensuring that the LVs have the most dominant ability to explain the dependent variables [39].

In this study, a regression model was constructed for each soil color group, including group one (10YR Value 3-5), group two (10YR Value 6-7), group three (7.5YR Value 5-7), and group four (5YR Value 6-7). The NIR spectral data (1000 – 2,500 nm) were used as the independent variable, while the N, P, and K contents were used as the dependent variables. The LVs were extracted from the independent variables related to the dependent variables [40]. The established calibration models were assessed and quantified by validating using cross-validation. The model performance was then evaluated using statistical parameters such as the coefficient of determination (R^2) and root mean square error (RMSE). R^2 reflects the model's ability to interpret sample spectra, while RMSE refers to the errors between the predicted and actual nutrient contents. Generally, the closer the R^2 value is to 1, the closer the RMSE value is to 0, indicating better model performance [41].

3. Results and Discussion

3.1 Effects of soil color on spectral behavior

The spectral behavior of soil varies depending on a combination of factors such as reflectance intensity (albedo), absorption features (depth and amplitude), and spectral shape. These characteristics are influenced by the soil's physical, chemical, and mineralogical properties [42]. The absorbance behavior of four soil color groups is shown in Figure 1. The spectra of group one soil color (10YR 3-5) had a higher absorbance when compared to group two, group three, and group four. Based on the studies of soil series characters in group one samples, it is demonstrated that the soil is fine-textured soil (higher clay content) and poorly drained, adversely affecting the soil's color and resulting in a darker hue. The differences in soil particle size were the primary cause of the variations in absorbance intensity, where soils with higher clay content showed more absorbed energy across the spectrum [43]. The spectral characters of Group Two, Group Three, and Group Four have a similar and low absorbed energy compared to Group One. This shows that groups two, three, and four had a higher sand content than group one.

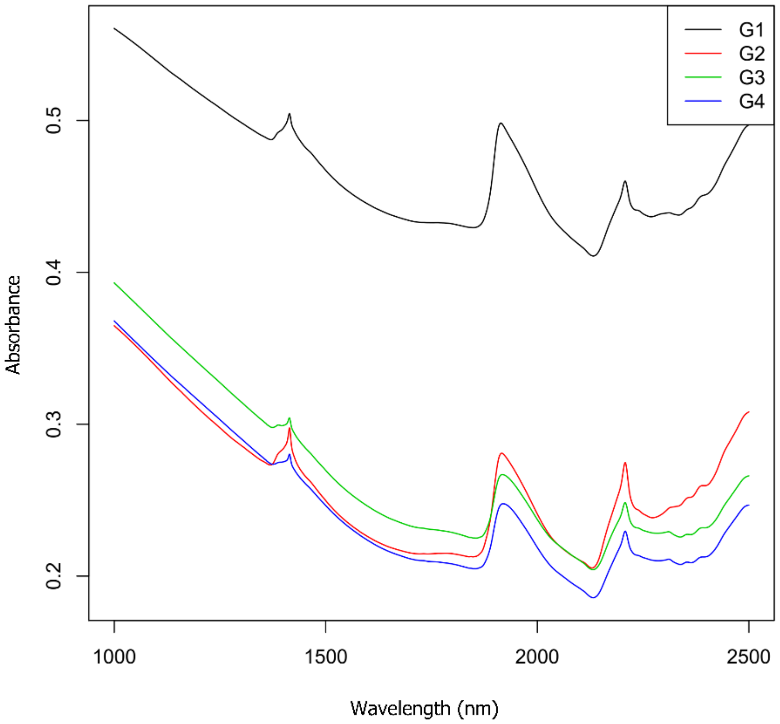

Figure 1. Spectra of the four soil color groups
G1 = soil color group one (10YR 3-5)
G2 = soil color group two (10YR 6-7)
G3 = soil color group three (7.5YR 5-7)
G4 = soil color group four (5YR 6-7)

However, the spectra of the four soil colors had similar behavior. The spectra exhibited robust absorption peaks at 1,400, 1,900, and 2,200 nm, attributed to molecular vibrations of hydroxyl (OH^-) groups [44, 45]. The absorption feature at 1,900 nm was more pronounced, possibly due to water (H_2O) in interstratified minerals [46]. Whiting et al. [45] have suggested that a stronger absorption intensity at 1,900 nm indicates the prevalence of structural H_2O in 2:1 minerals, such as montmorillonite and vermiculite. The absorption feature at 2,200 nm indicates kaolinite dominance [46]. The soil mineralogy has been characterized by 2:1 type clays, including illite, smectite, and vermiculite with hydroxy interlayers. However, most of the soil is dominated by 1:1-type clays [46–49]. The high activity of clay fraction (CFA) in some horizons was found to be associated with not only 2:1 clay but also 1:1 + 2:1 clay (interstratified minerals), as reported by [49].

Two types of minerals, namely 2:1 minerals or interstratified ones, exhibited a feature at 1400 nm, in addition to one sharper feature at 1900 nm and another with a more elongated shape at 2200 nm. The presence of both minerals simultaneously makes their identification difficult. However, in these soils, 2:1 clay minerals such as smectites and vermiculite are adsorbed at the surface by 1:1 minerals. The 2:1 minerals are found in the fine clay fraction (<0.2 mm) and are more likely to migrate in the soil due to the high content of exchangeable Na and Mg [46].

3.2 Accuracy of color to predict soil nutrients

Partial least squares regression (PLSR) analysis was performed on soil color and soil absorbance to predict the contents of total nitrogen (N), available phosphorus (P), and extractable potassium (K). The nutrient content prediction results for the four soil color groups are presented in Table 2. The modeling accuracy shows that the four soil color groups performed satisfactorily in predicting N, P, and K. The N prediction model showed an R^2 and RMSE ranging from 0.65 to 0.87 and 0.102 to 0.567 g kg^{-1}. The P prediction model showed an R^2 and RMSE ranging from 0.35 to 0.87 and 7.713 to 15.314 mg kg^{-1}, and the K prediction model showed an R^2 and RMSE ranging from 0.47 to 0.77 and 14.944 to 45.237 mg kg^{-1}. Moreover, our results show that the soil color in group two (10YR Value 6-7) was the best model to predict N. The R^2 values were 0.87, and the RMSE values were 0.131 g kg^{-1}. The soil color in group four (5YR Value 6-7) was the best model to predict P and K. The R^2 values were 0.87 and 0.77, and the RMSE values were 7.713 mg kg^{-1} and 14.944 mg kg^{-1}. The models show that the soil color can predict soil nutrients. It has been shown in many research. For example, Franzmeier [50] reported correlations between soil organic matter and Munsell value and chroma with R^2 values of 0.48. Lindbo et al. [51] used a chroma meter to measure soil color, organic carbon, and hydromorphology correlations. They reported an R^2 value of 0.63 for the correlation between dry Munsell value and soil organic carbon. Konen et al. [20] used a chroma meter to develop correlations between soil color, organic carbon, and texture. They showed logarithmic correlations between reflectance, Munsell value, Munsell chroma, and soil organic carbon. The R^2 values of their correlations ranged from 0.68 to 0.77. Moreover, Liles et al. [52] reported that soil type and parent materials influenced the lightness of the soil. They analyzed the relationship between the lightness of the soil and the total C content in forest soil around northern California. Their findings demonstrated that the R^2 for the relationship between soil C% and the lightness value varied with different soil types and parent materials. For instance, the R^2 values were 0.34 for all samples, 0.83 for Inceptisols, 0.6 for Andisols, 0.036 for Alfisols, and 0.35 for Ultisols. Schulze et al. [21] highlighted those variations in regression equations that were significantly influenced by soil texture and landscape. Attempting to predict nutrient contents across diverse soil types and landscapes using a single equation is often challenging. Within a specific landscape, the primary soil-forming factors include topography and the texture of the parent material. However, when considering broader landscapes, the key factors shift to encompass parent materials and vegetation.

Table 2. Accuracy of the prediction model based on soil color for the three soil properties.

Soil color group	Soil nutrients	R^2	RMSE
Group one (10YR Value 3-5)	N	0.75	0.146
	P	0.80	15.314
	K	0.50	45.237
Group two (10YR Value 6-7)	N	0.87	0.131
	P	0.44	10.456
	K	0.67	15.102
Group three (7.5YR Value 5-7)	N	0.65	0.567
	P	0.35	8.000
	K	0.47	29.659
Group four (5YR Value 6-7)	N	0.84	0.102
	P	0.87	7.713
	K	0.77	14.944

R^2 = coefficient of determination
RMSE = root mean square error
N = total nitrogen (g kg^{-1})
P = available phosphorus (mg kg^{-1})
K = extractable potassium (mg kg^{-1})

4. Conclusion

The NIR models we developed for predicting soil nutrient contents (total nitrogen, available phosphorus, and extractable potassium) use soil color as a predictor. The prediction of total nitrogen content in soil color group two (10YR Value 6-7) outperformed the prediction for total nitrogen in other soil color groups. For available phosphorus and extractable potassium, the best predictions were obtained from soil color group four (5YR Value 6-7). This demonstrates that combining NIRs with soil color can predict soil nutrient contents accurately. This method is efficient and nondestructive. It serves as an alternative to traditional approaches. In addition, although the model produced accurate predictions, its accuracy and robustness for future practical applications need to be validated in other study areas with more samples.

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References

[1] Cohen, M.J.; Prenger, J.P.; DeBusk, W.F. Visible-Near Infrared Reflectance Spectroscopy for Rapid, Nondestructive Assessment of Wetland Soil Quality. *J. Environ. Qual.* **2005**, *34*, 1422–1434. https://doi.org/10.2134/jeq2004.0353

[2] Viscarra Rossel, R.A.; Walvoort, D.J.J.; McBratney, A.B.; Janik, L.J.; Skjemstad, J.O. Visible, near infrared, mid infrared or combined diffuse reflectance spectroscopy for simultaneous assessment of various soil properties. *Geoderma*. **2006**, *131*, 59–75. https://doi.org/10.1016/j.geoderma.2005.03.007

[3] Blanco, M.; Villarroya, I. NIR spectroscopy: A rapid-response analytical tool. *TrAC - Trends Anal. Chem.* **2002**, *21*, 240–250. https://doi.org/10.1016/S0165-9936(02)00404-1

[4] Batten, G.D. Plant analysis using near infrared reflectance spectroscopy: The potential and the limitations. Aust. *J. Exp. Agric.* **1998**, *38*, 697–706 . https://doi.org/10.1071/EA97146

[5] He, Y., Huang, M., García, A., Hernández, A., Song, H.: Prediction of soil macronutrients content using near-infrared spectroscopy. *Comput. Electron. Agric.* **2007**, *58*, 144–153. https://doi.org/10.1016/j.compag.2007.03.011

[6] Johnson, J.M.; Sila, A.; Senthilkumar, K.; Shepherd, K.D.; Saito, K. Application of infrared spectroscopy for estimation of concentrations of macro- and micronutrients in rice in sub-Saharan Africa. *F. Crop. Res.* **2021**, *270*, 108222. https://doi.org/10.1016/j.fcr.2021.108222

[7] Kim, Y.J.; Choi, C.H. The analysis of paddy soils in Korea using visible-near infrared spectroscopy for development of real-time soil measurement system. *J. Korean Soc. Appl. Biol. Chem.* **2013**, *56*, 559–565. https://doi.org/10.1007/s13765-013-3067-z

[8] Malmir, M.; Tahmasbian, I.; Xu, Z.; Farrar, M.B.; Bai, S.H. Prediction of soil macro- and micro-elements in sieved and ground air-dried soils using laboratory-based hyperspectral imaging technique. *Geoderma*. **2019**, *340*, 70–80. https://doi.org/10.1016/j.geoderma.2018.12.049

[9] Salazar, O.; Benvenuto, A.; Fajardo, M.; Fuentes, J.P.; Nájera, F.; Celedón, A.; Pfeiffer, M.; Renwick, L.L.R.; Seguel, O.; Tapia, Y.; Casanova, M. Evaluation of a miniaturized portable NIR spectrometer for the prediction of soil properties in Mediterranean central Chile. *Geoderma Reg.* **2023**, *34*, e00675. https://doi.org/10.1016/j.geodrs.2023.e00675

[10] Peng, Y.; Zhao, L.; Hu, Y.; Wang, G.; Wang, L.; Liu, Z. Prediction of soil nutrient contents using visible and near-infrared reflectance spectroscopy. ISPRS Int. *J. Geo-Information.* **2019**, *8*. https://doi.org/10.3390/ijgi8100437

[11] Munawar, A.A.; Yunus, Y.; Devianti, Satriyo, P. Calibration models database of near infrared spectroscopy to predict agricultural soil fertility properties. *Data Br.* **2020**, *30*, 105469. https://doi.org/10.1016/j.dib.2020.105469

[12] Ibáñez-Asensio, S.; Marqués-Mateu, A.; Moreno-Ramón, H.; Balasch, S. Statistical relationships between soil colour and soil attributes in semiarid areas. *Biosyst. Eng.* **2013**, *116*, 120–129. https://doi.org/10.1016/j.biosystemseng.2013.07.013

[13] Ketterings, Q.M.; Bigham, J.M. Soil Color as an Indicator of Slash-and-Burn Fire Severity and Soil Fertility in Sumatra, Indonesia. *Soil Sci. Soc. Am. J.* **2000**, *64*, 1826–1833. https://doi.org/10.2136/sssaj2000.6451826x

[14] Schmidt, S.A.; Ahn, C. Analysis of soil color variables and their relationships between two field-based methods and its potential application for wetland soils. *Sci. Total Environ.* **2021**, *783*, 147005. https://doi.org/10.1016/j.scitotenv.2021.147005

[15] Christensen, L.K.; Bennedsen, B.S.; Jørgensen, R.N.; Nielsen, H. Modelling nitrogen and phosphorus content at early growth stages in spring barley using hyperspectral line scanning. *Biosyst. Eng.* **2004**, *88*, 19–24. https://doi.org/10.1016/j.biosystemseng.2004.02.006

[16] Schwertmann, U. Relations between iron oxides, soil color, and soil formation. Soil Color. Proc. *Symp. San Antonio*. **1993**. 51–69.

[17] Simonson, R.W. Soil color standards and terms for field use-history of their development. Madison: Soil Society of America. **1993**.

[18] Torrent, J., Barrón, V.: The visible diffuse reflectance spectrum in relation to the color and crystal properties of hematite. *Clays Clay Miner.* **2003**, *51*, 309–317. https://doi.org/10.1346/CCMN.2003.0510307

[19] Brady, N.C.; Weil, R.R. The nature and properties of soils. New Jersey Prentice Hall. **2006**.

[20] Konen, M.E.; Burras, C.L.; Sandor, J.A. Organic Carbon, Texture, and Quantitative Color Measurement Relationships for Cultivated Soils in North Central Iowa. *Soil Sci. Soc. Am. J.* **2003**, *67*, 1823–1830. https://doi.org/10.2136/sssaj2003.1823

[21] Schulze, D.G.; Nagel, J.L.; Van Scoyoc, G.E.; Henderson, T.L.; Baumgardner, M.F.; Stott, D.E. Significance of organic matter in determining soil colors. , Madison: Soil Society of America. 1993.

[22] Munsell Color: Munsell Soil Color Charts, **2000**, Revised Washable Edition. , Gretagmacbeth, New Windsor, NY.

[23] Soil Science Division Staff. Soil survey manual. C. Ditzler, K. Scheffe, and H.C. Monger (eds.). USDA Handbook 18. , Government Printing Office, Washington, D.C. **2017**.

[24] Stoner, E.R.; Baumgardner, M.F. Characteristic Variations in Reflectance of Surface Soils. *Soil Sci. Soc. Am. J.* **1981**, *45*, 1161–1165. https://doi.org/10.2136/sssaj1981.03615995004500060031x

[25] Baumgardner, M.F.; Silva, L.R.F.; Biehl, L.L.; Stoner, E.R. Reflectance properties of soils. *Adv. Agron.* **1986**, 38, 1–44. https://doi.org/10.1016/S0065-2113(08)60672-0

[26] Shields, J.A.; Paul, E.A.; Arnaud, R.J.S.; Head, W.K. Spectrometric Measurment of Soil Color and its Relationship to Moisture and Organic Matter. *Can. J. Sci.* **1968**, *48*, 271–280.

[27] Condit, H.R. Spectral Reflectance of American Soils. *Photogramm Eng.* **1970**, *36*, 955–966.

[28] Moritsuka, N.; Matsuoka, K.; Katsura, K.; Sano, S.; Yanai, J. Soil color analysis for statistically estimating total carbon, total nitrogen and active iron contents in Japanese agricultural soils. *Soil Sci. Plant Nutr.* **2014**, 60, 475–485. https://doi.org/10.1080/00380768.2014.906295

[29] Mouazen, A.M.; Karoui, R.; Deckers, J.; De Baerdemaeker, J.; Ramon, H. Potential of visible and near-infrared spectroscopy to derive colour groups utilising the Munsell soil colour charts. *Biosyst. Eng.* **2007**, *97*, 131–143. https://doi.org/10.1016/j.biosystemseng.2007.03.023

[30] Gholizadeh, A.; Saberioon, M.; Viscarra Rossel, R.A.; Boruvka, L.; Klement, A. Spectroscopic measurements and imaging of soil colour for field scale estimation of soil organic carbon. *Geoderma.* **2020**, *357*, 113972. https://doi.org/10.1016/j.geoderma.2019.113972

[31] Viscarra Rossel, R.A.; Fouad, Y.; Walter, C. Using a digital camera to measure soil organic carbon and iron contents. *Biosyst. Eng.* **2008**, *100*, 149–159. https://doi.org/10.1016/j.biosystemseng.2008.02.007

[32] Jackson, P.E.; Krol, J.; Heckenberg, A.L.; Mientijes, M.; Staal, W. Determination of total nitrogen in food, environmental and other samples by ion chromatography after Kjeldahl digestion. *J. Chromatogr. A.* **1991**, *546*, 405–410. https://doi.org/10.1016/S0021-9673(01)93039-0

[33] Bray, R.H.; Kurtz, L.T.: Determination of total, organic and available forms of phosphorus in soils. **1945**.

[34] Jackson, K.W.; Chen, G. Atomic absorption, atomic emission, and flame emission spectrometry. *Anal. Chem*. **1996**, *68*, 231–256. https://doi.org/10.1021/a1960012l

[35] Shao, Y.; He, Y. Nitrogen, phosphorus, and potassium prediction in soils, using infrared spectroscopy. *Soil Res*. **2011**, *49*, 166–172. https://doi.org/10.1071/SR10098

[36] Pudełko, A.; Chodak, M. Estimation of total nitrogen and organic carbon contents in mine soils with NIR reflectance spectroscopy and various chemometric methods. *Geoderma*. **2020**, *368*. https://doi.org/10.1016/j.geoderma.2020.114306

[37] Chen, Z.; Ren, S.; Qin, R.; Nie, P. Rapid Detection of Different Types of Soil Nitrogen Using Near-Infrared Hyperspectral Imaging. *Molecules*. **2022**, *27*, 2017. https://doi.org/10.3390/molecules27062017

[38] Wold, S.; Martens, H.; Wold, H. A multivariate calibration problem in analytical chemistry solved by the PLS method. *Lect. Notes Math.* **1983**, *46*, 286–293.

[39] Wang, H.; Liu, Q.; TU, Y. Identification of Optimal Subspace from PLS Regression. *J. Beijing Univ.* Aeronaut. Astronaut. (In China). **2000**, *26*, 473.

[40] Zhang, Y., Li, M.Z., Zheng, L.H., Zhao, Y., Pei, X.: Soil nitrogen content forecasting based on real-time NIR spectroscopy. *Comput. Electron. Agric.* **2016**, *124*, 29–36. https://doi.org/10.1016/j.compag.2016.03.016

[41] He, H.J.; Wu, D.; Sun, D.W. Rapid and non-destructive determination of drip loss and pH distribution in farmed Atlantic salmon (Salmo salar) fillets using visible and near-infrared (Vis-NIR) hyperspectral imaging. *Food Chem*. **2014**, *156*, 394–401. https://doi.org/10.1016/j.foodchem.2014.01.118

[42] Demattê, J.A.M. Characterization and discrimination of soils by their reflected electromagnetic energy. *Pesqui. Agropecu. Bras*. **2002**, *37*, 1445–1458. https://doi.org/10.1590/S0100-204X2002001000013

[43] Sørensen, L.K.; Dalsgaard, S. Determination of Clay and Other Soil Properties by Near Infrared Spectroscopy. *Soil Sci. Soc. Am. J. 2005*, 69, 159. https://doi.org/10.2136/sssaj2005.0159

[44] Stenberg, B.; Viscarra Rossel, R.A.; Mouazen, A.M.; Wetterlind, J. Visible and Near Infrared Spectroscopy in Soil Science. *Adv. Agron.* **2010**, *107*, 163–215. https://doi.org/10.1016/S0065-2113(10)07005-7

[45] Whiting, M.L.; Li, L.; Ustin, S.L. Predicting water content using Gaussian model on soil spectra. *Remote Sens. Environ*. **2004**, *89*, 535–552. https://doi.org/10.1016/j.rse.2003.11.009

[46] Demattê, J.A.M.; Horák-Terra, I.; Beirigo, R.M.; Terra, F. da S.; Marques, K.P.P.; Fongaro, C.T.; Silva, A.C.; Vidal-Torrado, P. Genesis and properties of wetland soils by VIS-NIR-SWIR as a technique for environmental monitoring. *J. Environ. Manage.* **2017**, *197*, 50–62. https://doi.org/10.1016/j.jenvman.2017.03.014

[47] Nascimento, A.F. do; Furquim, S.A.C.; Couto, E.G.; Beirigo, R.M.; Oliveira Júnior, J.C. de; Camargo, P.B. de; Vidal-Torrado, P. Genesis of textural contrasts in subsurface soil horizons in the Northern Pantanal-Brazil. *Rev. Bras. Ciência do Solo.* **2013**, *37*, 1113–1127. https://doi.org/10.1590/s0100-06832013000500001

[48] Nascimento, A.F.; Furquim, S.A.C.; Graham, R.C.; Beirigo, R.M.; Oliveira Junior, J.C.; Couto, E.G.; Vidal-Torrado, P. Pedogenesis in a Pleistocene fluvial system of the Northern Pantanal - Brazil. *Geoderma.* **2015**, 58–72. https://doi.org/10.1016/j.geoderma.2015.04.025

[49] De Arruda Oliveira Coringa, E.; Couto, E.G.; Torrado, P.V. Soil geochemistry of the northern pantanal, mato grosso, Brazil. *Rev. Bras. Cienc. do Solo*. **2014**, *38*, 1784–1793. https://doi.org/10.1590/s0100-06832014000600013

[50] Franzmeier, D. Relation of Organic Matter Content to Texture and Color of Indiana Soils. *1998*.

[51] Lindbo, D.L.; Rabenhorst, M.C.; Rhoton, F.E. Soil color, organic carbon, and hydromorphology relationships in sandy epipedons. *Quantifying Soil Hydromorphology*. **1998**, *54*, 95–105. https://doi.org/10.2136/sssaspecpub54.c6

[52] Liles, G.C.; Beaudette, D.E.; O'Geen, A.T.; Horwath, W.R. Developing predictive soil C models for soils using quantitative color measurements. *Soil Sci. Soc. Am. J.* **2013**, *77*, 2173–2181. https://doi.org/10.2136/sssaj2013.02.0057