Near Infrared Technology in Agricultural Sustainability: Rapid Prediction of Nitrogen Content from Organic Fertilizer

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In order to support agricultural sustainability, rapid and precise method needs to be applied for resources efficiency. Presented study employs the near infrared reflectance (NIRS) as a rapid and effective sensing technology in detecting and determining quality parameter of organic fertilizer in form of nitrogen content (N). a total of 10 organic fertilizers were used as samples made from agricultural waste. Near infrared spectra data were acquired and measured as absorbance for all samples in wavenumbers range 5,000 – 11,000 cm-1. On the other hand, actual N content was measured by means of standard laboratory procedures. Spectra data were corrected using de-trending second order (DT-2), standard normal variate (SNV) and combination of them (SNV+DT). Moreover, prediction models for N content determination were developed using principal component regression (PCR) followed by leverage cross validation. The results showed that N content can be predicted rapidly without involving chemical materials with maximum coefficient of determination are 0.98 for calibration and 0.95 for validation phase respectively. Spectra correction was highly affected the prediction performance and can improve prediction accuracy. The combination spectra correction SNV+DT increase the prediction up to 0.95 from previously 0.90. Therefore, It would be better if the spectra data were corrected and enhanced prior to prediction modelling to improve the performance. Based on obtained results, it may conclude that sensing technology based on NIRS can be applied to support agriculture sustainability as a rapid and effective method for N determination of organic fertilizers.

Keywords: Agriculture, NIRS, organic, resources, soil.

1 Introduction

Agricultural sustainability development is essential in the most of developing countries improve land production and conservation of natural resources. The development agricultural sustainability practices and increase of production in farming system is inseparable from the interaction factors of each component involved in it. Inputs given to the farming system can come from outside or from the farming system through recycling of nutrients from agricultural waste in the form of compost products or animal feed. Recycling of nutrients in the farming system is a key factor in maintaining its sustainability (Hong et al., 2019; Yu et al., 2018). The problem faced in treating agricultural waste is the low level of farmers' knowledge of the benefits of waste. Different community perceptions of the existence of the waste resulted in slow handling of the waste. Some people are of the opinion that managing waste is a work that is not important to do, does not provide benefits, and it is time consuming. The public perception must be changed to see the amount of waste that continues to grow every year. Addition of waste that is not in accordance with the level of management has a very bad impact on the sustainability of agriculture in Indonesia (Agus Arip Munawar, Yunus, Devianti, & Satriyo, 2020; Yunus, Devianti, Satriyo, & Munawar, 2019).

Agricultural sustainable management receives considerable support and acceptance within agriculture prevailing, depending on some environmental concerns. Utilization of agricultural waste can help farmers overcome the problem of shortages for organic fertilizer. Straw produced from harvesting can be dried and stored to be used as material for making organic fertilizer. Horticultural crops such as vegetables are also very well used for making compost. That the most crop production is rice. Rice production of 19,134 quintals with a planting area of 3,045 hectares and a harvesting area of 2,511 hectares produces 4-5 tons of hay/ha. Rice straw is one alternative to offset the shortage of farmers for animal feed purposes (Devianti, Sufardi, Zulfahrizal, & Munawar, 2019; Devianti, Yusmanizar, Syakur, Munawar, & Yunus, 2021)

In general, the condition of agricultural land in Indonesia has experienced a decline in fertility and soil damage and consequently, has a decline in agricultural crops productivity, especially intensification of paddy fields. The causes include: a) imbalance of nutrient content in the soil; b) drainage and nutrient deficits; c) decrease in soil organic matter content; d) silting of the flow tread layer; e) pollution by agrochemicals or waste; f) decrease in population and microbial activity. As a result of unwise management of nutrients, most of the paddy fields are indicated to have very low levels of organic matter (C-organic ¡2%). About 65% of the 7.9 million ha of paddy fields in Indonesia have low to very low organic matter content (C-organic ¡2%), around 17% have low total soil P levels and around 12% have low total K levels. In the intensification of paddy fields, an increasingly shallow layer of tillage was encountered so that the roots of rice plants could not develop properly (Meer, 2018; Wan et al., 2019; Yu et al., 2018). The sustainable agriculture practices can be considered to maintain foods and agricultural production without causing environmental pollutions.

The use of fertilizers in dry land generally uses inadequate doses, so it is suspected that nutrient depletion occurs. In addition, the use of compost or return the rest of the harvest to agricultural land is almost not done. Especially for dry land in sloped areas, not yet implementing ideal soil conservation measures, resulting in erosion and high surface runoff. The impact of erosion causes nutrient content and organic material to move to lower land. To reduce the deterioration of soil fertility and increase the productivity of sustainable yields it is necessary to use adequate compost fertilizer in quantity, quality and continuity. Plant requires compost with different nutrients, therefore farmers must provide compost with nutrients according to the needs of the plant (Hong et al., 2019; Sun, Zhang, Sun, Sun, & Cen, 2018). The problem that is found at this time is not the amount of compost sold in the market and the nutrient content that has not been included in the compost, so that the farmers are not informed about the nutrient content that will be given to plants. Nutrient content in compost is usually known through laboratory testing, but if a laboratory test is carried out nutrient tests make us spend a lot of money and take a long time. With the sophistication of the modern era there is now a tool to make it easier for us to predict the content that is in both solid and liquid materials, namely near infrared reflectance spectroscopy (NIRS) technology (Baveye & Laba, 2015; Soriano-Disla, Janik, & McLaughlin, 2018). It is recognized and developed as a non-destructive method, can analyze at high speed, does not cause pollution, simple sample preparations and does not require any chemical materials.

In the practices and applications of near infrared reflectance spectroscopy, multivariate analysis plays an important role in analysing overlapping spectral data. They were obtained from the near infrared spectrophotometers not only contain sample information but also contain background and noises (Deng, Wang, Zhong, & Yu, 2018; Pasquini, 2018). Therefore, it is necessary to pre-process before building the calibration model. Pre-processing is a step of data transformation to improve the spectrum that is not good due to the blending of light when the acquisition of near infrared data, noise, interference from the outer circle and other problems that cause the information contained in the spectrum to be difficult to analyze.

Numerous studies have been reported in related to the application of NIRS technology in many fields, especially in agriculture like fruit quality evaluation (Jha et al., 2012; Agus Arip Munawar, von Hörsten, Wegener, Pawelzik, & Mörlein, 2016; Nagle, Mahayothee, Rungpichayapichet, Janjai, & Müller, 2010), animal feed quality parameters prediction (Samadi, Wajizah, & Munawar, 2018), cocoa and coffee quality in intact green bean form (León-Roque, Abderrahim, Nuñez-Alejos, Arribas, & Condezo-Hoyos, 2016; Sunoj, Igathinathane, & Visvanathan, 2016; Teye, Huang, Dai, & Chen, 2013), soil quality attributes prediction and other biological material properties (Johnson et al., 2019; Shi, Wang, Chen, & Wu, 2016). Thus, the main purpose of this present study is to apply the NIRS technology in determining N content of organic fertilizers made from recycled agricultural waste. The prediction models were established using PCR regression approach with different spectra correction algorithms models (Pasquini, 2018).

2 Materials and Methods

Spectra Data

The near infrared spectrum for all compost samples were acquired and obtained using portable near infrared spectroscopy instruments (PSD NIRS, iptek i16) with workflow configurations built using an integrated software namely Thermo Integration®. Workflow is made to acquire absorbance spectrum and scan samples 27 times (A A Munawar, Yunus, Devianti, & Satriyo, 2021; Agus Arip Munawar, Devianti, Satriyo, Syahrul, & Yunus, 2019). Each sample is measured in three different points, then averaging the results and storing those spectral data in two file formats.

Samples

Organic fertilizers were made from un-used agricultural waste with detailed compositions is described in Table 1.

Table 1: Composting materials used as fertilizer samples

Compost materials	Percentage
Straw + cow manure	50%+25%
Straw + goat manure	50%+25%
Straw + chicken manure	50%+25%
Straw + corn + cow manure	50%+25%+25%
Straw + corn + goat manure	50%+25%+25%
Straw + corn + chicken manure	50%+25%+25%
Corn + cow manure	50%+25%
Corn + goat manure	50%+25%
Corn + chicken manure	50%+25%

Actual Nitrogen Measurement

After obtaining spectra data, all samples were taken to the lab for actual N content measurement. It was conducted using Kjeldahl method and measured in triplicate, then averaged. The actual nitrogen content was used as a verification data in calibration and validation phases (Biancolillo, Firmani, Bucci, Magrì, & Marini, 2019; Hong et al., 2018).

Spectra Data Corrections

Before being used for data analysis (building prediction models), the NIR spectrum for all compost samples was corrected. This aims of this step is to eliminate various kinds of "noises" in the compost sample spectrum so that the prediction results are more accurate and robust (Arendse, Fawole, Magwaza, & Opara, 2018; Pasquini, 2018). The methods used in this spectra corrections are: de-trending second order (DT-2), standard normal variate (SNV), and combination of them (SNV+DT) (Agus Arip Munawar, Devianti, Satriyo, & Yunus, 2019).

Prediction Models

The nitrogen content in organic fertilizer were predicted based on NIR spectral data (raw and corrected) through calibration process and followed by leverage cross validation. Prediction models were built by regressing the NIR spectrum (variable X) with the actual N content (variable Y) from the measurement results in the laboratory (Comino, Aranda, García-Ruiz, Ayora-Cañada, & Domínguez-Vidal, 2018; Pasquini, 2018). The calibration method that were used in this phase is the principal component regression (PCR). All data analysis including spectra corrections and prediction models development were carried out using The Unscrambler X 10.3 Software (CAMO Oslo, Norway) with network client licensed. Justification of the model (accuracy and robustness) is evaluated based on statistical parameters, namely: correlation coefficient (r) or coefficient of determination (R2) between the prediction results and actual measurement and ratio prediction to deviation (RPD) (Pasquini, 2018).

3 Results and Discussion

In general, materials that are subjected to near infrared spectroscopy radiation with presented wavenumber received energy that triggers vibrations in the OH, NH, and CH atomic bonding groups which are the main components of the formation of organic compounds and as a result of molecular bond interactions can indicate the fertilizer chemical content and nutrition.

Some of the energy were absorbed and some will be reflected. Energy that is emitted into organic material, around 4% were reflected back to the outer surface and around 96% were entered the material and then experience absorption, reflection, diffusion and the transmission of light. Radiation on the sample will occur three radiation phenomena, namely absorbed, transmitted, and reflected. In this study the acquisition process uses a wavenumbers range from 5000 to 11000 cm-1. The spectra feature of the organic fertilizer made from the agricultural waste is presented in Fig. 1.

As shown in Fig.1, the raw spectrum appeared still tenuous the presence of noise at the time of measurement using near infrared spectroscopy. Then it is necessary to perform spectra correction in order to reduce the noise and error that occurs in the generated NIRS waves. Principal component regression (PCR) regression method is a method with a working principle that is the reduction of variables using the principal component. The advantage of this type of regression is the reduced number of predictor variables used for calibration than the number of original variables. The results of the construction of the calibration model using the PCR method produce a model in form of unsb extension files. The PCR method works in conjunction with a black box system where the workings occur within the software. Prediction performance of N content using raw untreated spectra data is presented in Fig.2.

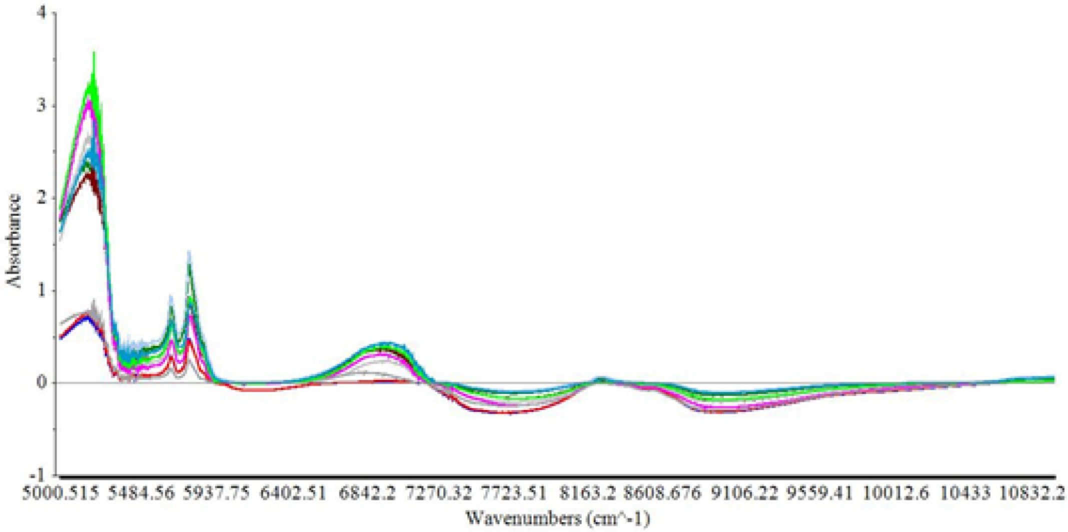

Figure 1: *Spectra feature of organic fertilizer samples in NIR region.*

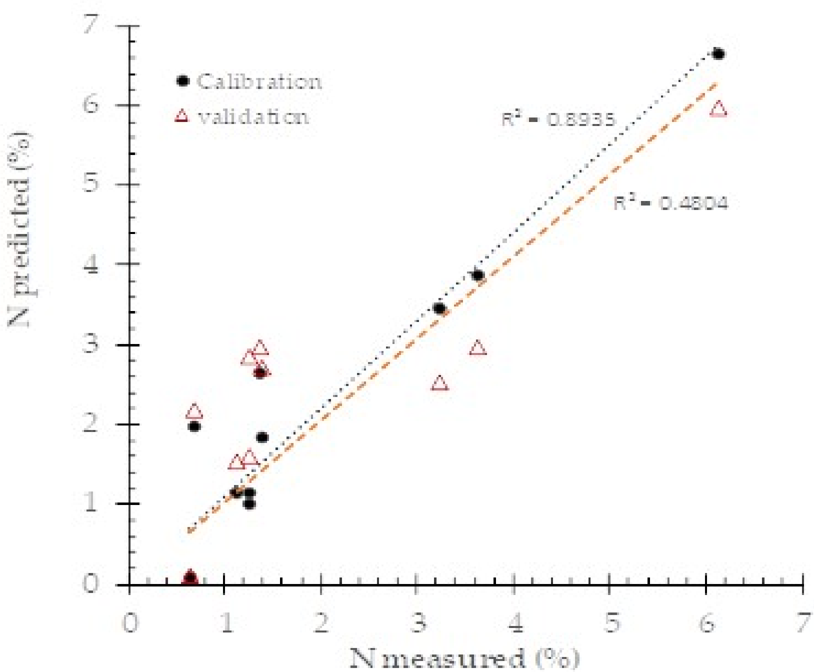

Figure 2: *The N content prediction performance using raw spectra data.*

The prediction results of raw spectra data for N content prediction using NIRS can be seen that there are quite close to the actual N content measurement with R2 = 0.89 in calibration. Meanwhile, during validation, the R2 is 0.48. In brief, the determination coefficient refers to how large data can be predicted accurately using near infrared method. The higher coefficient determination the better. The determination coefficient 0.89 means 89% of all presented data of N content can be predicted by NIRS. There are some values are different from the results of laboratory tests. The difference between the laboratory test with the

NIRS prediction with the standard normal variate is 0.31%, while with the L3 sample code the difference is 1.77%. The accuracy of N content prediction on compost can be evaluated with statistical parameters such as, correlation coefficient (r), coefficient of determination (R2), root mean square error (RMSE), ratio prediction to deviation (RPD) Index, and number of latent variables (LV). When the models were developed using corrected spectra data like DT-2 and SNV, the prediction performance becomes better than raw un-corrected spectral data as shown in Fig.3 and Fig.4 respectively.

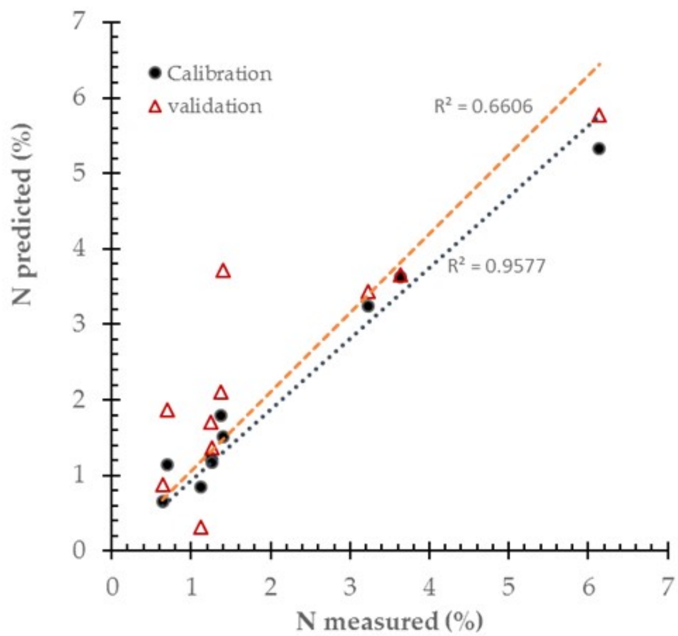

Figure 3: *The N content prediction performance using DT-2 spectra data.*

The prediction performance was improved when the model is constructed using corrected spectral data. As shown in Fig.3 above, the coefficient of determination is increase to 0.95 in calibration and 0.66 in validation phase respectively. It is obvious that spectra correction is necessary to be performed in order to achieve good prediction results. It also happened when the model is developed using the SNV spectra data.

The multivariate calibration technique begins with PCA then continues with a regression between the new main components and the response. When predictive variables are not interconnected, this technique is useless. The reduced variable in this case is a prediction variable using the main component (principal component, PC) derived from the Principal component analysis (PCA) grouping method compared to the original variable. This respective method also can be used to detect outlier data on the dataset in combination with Hotelling t2 ellipse as shown in Fig.5.

The advantage of this type of regression is the reduced number of predictor variables used for calibration rather than the number of original variables. However, PCR only considers the correlation of predicted variables with the main component (PC) without regard to the strength of the relationship with the response variable. Principal component regression (PCR) is a multivariate calibration method for analyzing statistics of multiple variables that can be used for the purpose of reducing a number of original variables to new orthogonal variables and not reducing and still maintaining a large total diversity of original variables. Thus, calibration regression can be built using the principal component regression method.

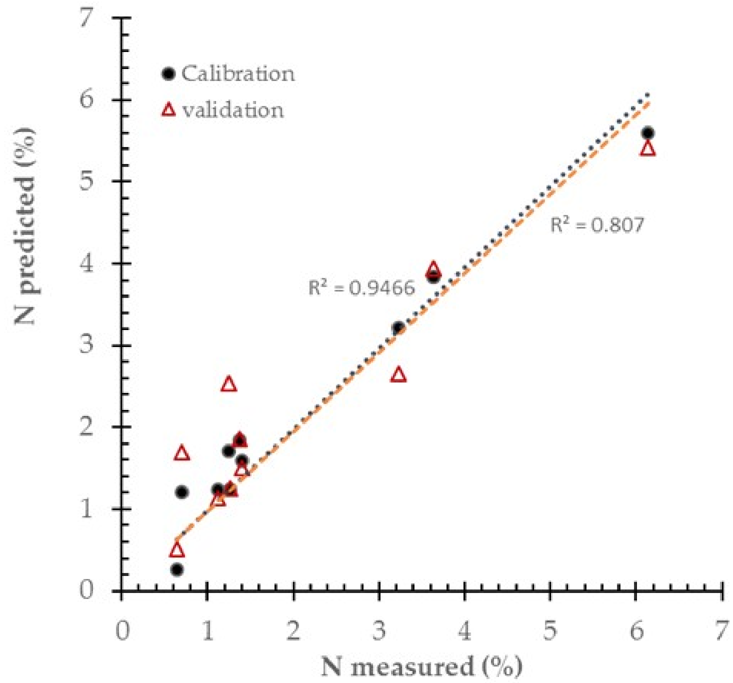

Figure 4: *The N content prediction performance using SNV spectra data.*

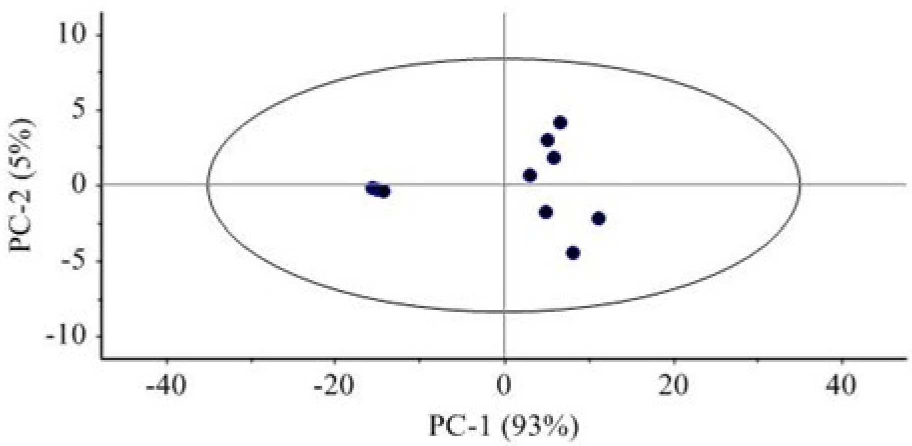

Figure 5: *The PCA and Hotelling t^2 ellipse to detect outlier data in raw spectrum.*

It was also mentioned that three main factors were taken into account in the NIR spectroscopy test sample technique, namely particle size, moisture content, and temperature of the material being tested. Furthermore, diffuse reflectance and transmittance of NIR spectra is the result of a condition of the combination of the instrument and the sample or material used, namely the geometry or shape of the instrument, the size of the material being tested (in the form of particles or point of testing), form and distribution of materials when testing and others. Prediction performance was more even better when two spectra correction methods are combined as shown in Fig.6.

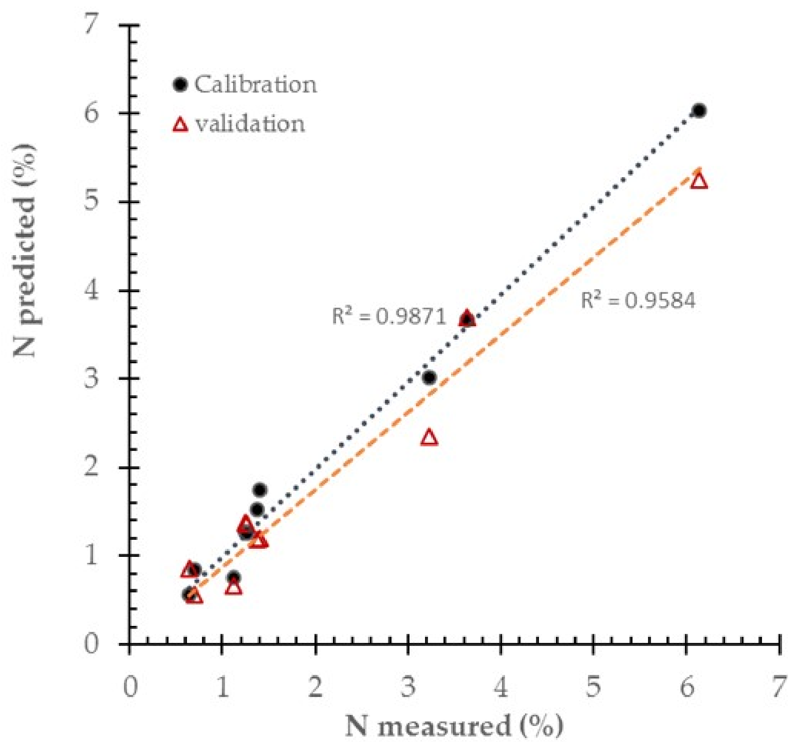

Figure 6: *The N content prediction performance using SNV+DT spectra data.*

After the calibration regression model is obtained, a validation step is carried out using the rest of the data. The different sample data is entered into the calibration regression, so that the composition of physical data is obtained. Validation aims to test the accuracy of estimation of chemical composition with calibration regression that has been built. Near infrared which affects the material has little energy and only penetrates about one millimetre of the surface of the material, depending on the composition of the material. If the light is scattered, the spectrum still contains information, for example the absorption of the surface of the material but distortion occurs at the peak of the wave. Variations in the size and temperature of sample particles affect the spread of near infrared radiation as they pass through the sample. Large particles cannot spread near infrared radiation as much as small particles. The more radiation absorbed, the higher the absorbance value will be and the greater the wavelength absorbed. When near infrared radiation hits a solid sample, part of the radiation will be reflected (specular reflectance) from the sample surface. If radiation enters a sample which has a thickness of around 2 mm it will be absorbed. Radiation that is not absorbed can be transmitted through samples or reflected.

The near infrared reflectance spectroscopy is based on the electromagnetic energy located at a wavelength of 780 - 2500 nm or in wavenumbers 4,000 - 12,500 cm-1 and contains more complex information structures because of the combination of bonding patterns. The recording region of the NIRS electromagnetic wave is a response from the bonding of O-H, C-H, C-O and N-H molecules. 10 This bond causes changes in vibrational energy when irradiated by NIRS frequencies, like stretching and bending vibrations. Based on obtained results, it showed that N content can be predicted rapidly and effectively without involving chemical materials with maximum coefficient of determination are 0.98 for calibration and 0.95 for validation phase respectively. It may conclude that NIRS technology can be applied as a rapid and effective method for N determination of organic fertilizers made from agricultural waste.

4 Conclusions

Recycling of nutrients in the farming system is one of main factors in maintaining agricultural sustainability. Organic waste can be benefited and transformed onto organic fertilizers. The chemical quality parameters of these fertilizers can be determined rapidly using near infrared technology with easy sample preparations and without causing environmental pollutions. The prediction performance of the predicted models of Nitrogen content is achieved when the NIRS model is established by means of combined spectral data with maximum determination coefficient 0.98 in calibration and 0.95 in validation. Based on obtained results, it may conclude that sensing technology based on NIRS can be applied to support agriculture sustainability as a rapid and effective method for N determination of organic fertilizers.

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