Organic fertilizer from agricultural waste: determination of phosphorus content using near infrared reflectance

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Abstract. Agricultural waste can be converted onto useful materials like compost or organic fertilizers. In a simply practice, those wastes were kept and mixed with additional composting materials to enrich the fertilizer nutrients and compositions. Generally, plants can growth optimally in sufficient media, that is soil. It requires adequate micro and macro nutrients like phosphorus (P). in order to determine P content and other nutrient properties, many methods have been widely used from which most of them are wet chemical analysis. The main aim of this present study is to employ the near infrared reflectance (NIRS) technique in determining P content of organic fertilizer. Spectra data were generated in wavenumbers 5000–10 000 cm–1 and the model were established using principal component regression (PCR) method. The results showed that P content of compost materials can be determined using NIRS with maximum correlation coefficient 0.99 and robustness index 4.14 respectively.

1. Introduction
Agricultural waste is the residue from the main agricultural products such as food crops and horticulture, plantation crops, and livestock manure. Agricultural waste is defined as part of agricultural plants on the ground or part of shoots that remain after harvesting or the main results are taken. Agricultural waste that has been utilized for agricultural and plantation needs is only 30-40% of the available waste. This is considered to be very lacking considering the waste available at the time of abundant harvesting, innovation is needed to treat further waste so that it can be applied to farming [1]. Utilization of agricultural waste for farming is still low, farmers are accustomed to using chemical fertilizers to increase crop production. The high use of chemical fertilizers because it is always available in the market and is a mainstay of farmers in farming, but the use of sustainable chemical fertilizers can damage the fertility of the soil itself [2], [3]. Habits of farmers in the use of chemical fertilizers due to the lack of organic fertilizers on the market and for the contents that are in organic fertilizer are not listed so that farmers find it difficult to adjust to the needs of their crops.

Utilization of agricultural waste can help farmers overcome the problem of lack of organic fertilizer. Straw produced from harvesting is also very well used for organic fertilizer. The most crop production is paddy, paddy production as much as 19,134 quintals with a planting area of 3,045 ha and a harvest area of 2,511 ha producing 4-5 tons of hay / ha [4]. The problem faced in treating agricultural waste is the low level of farmers’ knowledge of the benefits of waste.

Agricultural waste as a source of organic material and soil nutrients, agricultural waste including plantations and livestock such as straw, crop residues or bushes, pet manure and the like are sources of organic material and plant nutrients. The waste can be directly placed on agricultural land or immersed for more effective results, the processing should be done first by mixing agricultural waste and weathering will occur [5], [6]. Weathering of agricultural wastes naturally takes more than 3-4 months, so that conservation efforts with the use of organic materials on agricultural lands experience obstacles. It will be more complicated if faced with an urgent planting period, so that it is often considered less economical and inefficient. One method of accelerating weathering of agricultural waste to immediately function in improving soil properties and nutrient availability is by making organic fertilizers.
Organic fertilizer is very beneficial for increasing agricultural production both in quality and quantity, can reduce environmental pollution, and improve land quality in a sustainable manner. The use of organic fertilizer in the long run can increase land productivity and can prevent land degradation. The sources of raw materials for organic fertilizers are very varied, such as agricultural and non-agricultural wastes with very diverse physical characteristics and chemical/nutrient contents, so the quality of organic fertilizers produced tends to vary [7], [8]. Livestock and agricultural waste, if not utilized will have an impact on the environment in the form of air, water and soil pollution, a source of disease, can spur increased methane gas and also disrupt the aesthetics and comfort. Cow dung is one of the potential ingredients for making organic fertilizer. A single cow per day produces manure ranging from 8-10 kg per day or 2.6 - 3.6 tons per year, equivalent to 1.5 - 2 tons of organic fertilizer so that it will reduce the use of inorganic fertilizers and speed up the process of land improvement [9], [10]. Manure is fertilizer derived from animal waste mixed with food scraps and urine which contains nutrients N, P, and K which can be used to improve soil fertility.

During last few decades, NIRS has been widely used and developed in many fields including agriculture and environment studies. Numerous applications related to this technique have been reported in the field of agriculture such as fruit and horticulture [11]–[13], meat and dairy products [14]–[16], soil evaluation [10], and agricultural crops quality prediction [17]–[19]. Therefore, the main aim of this present study is to employ the near infrared reflectance (NIRS) technique in determining P content of organic fertilizer. Prediction models were developed based on raw and enhanced spectra data using principal component regression.

2. Material and Methods
2.1 Spectra data measurement
Near infrared spectra data of organic fertilizers were measured using a portable sensing device (PSD-FTNIR i16) in wavenumbers range from 5000 to 10 000 cm\(^{-1}\). Optical gain was set to 4x and spectra data were acquired and recorded in absorbance format [20].

2.2 Spectra correction
It was performed to reduce the effect of noise wave interference on the obtained spectrum data in order to obtain a more accurate and stable robust model. Prior to the development of the analysis model, spectral data were corrected both in calibration and prediction data [21]. The effect of the emission correction that has been done can be seen by comparing the regression plot and the overall spectrum of the sample to the data that has been corrected using various methods: de-trending order 2 (DT order 2), standard normal variate (SNV) and combination between them (DT2 + SNV) respectively.

2.3 Actual P measurement
The actual measurement for phosphorus content of organic fertilizer samples were carried out in the laboratory by using the Bray and Kurtz method [22], [23]. This method is better known as the Bray method and is distinguished by Bray number 1 (0.025 N HCL + 0.3 N NH4F) and Bray number 2 (C.1 N HCL + 0.3 N NH4F). This method was generally developed for acid soils, but it is also good for neutral soils.

2.4 Prediction models
The phosphorus content of organic fertilizer was predicted based on the NIR spectra data obtained through prediction model development. The principal component regression (PCR) method was employed to establish those models [12], [13]. Prediction performances were evaluated by means of several statistical indicators, namely: correlation coefficient (r) between the predicted results with the results of standard measurements in the laboratory for P content and also ratio prediction to deviation index (PRD) of the predicted values.
3. Result and discussion

3.1 Organic fertilizer characteristics

Organic fertilizer resulted from the decomposition of organic materials both dry plants and livestock waste that can be broken down by microbes that are able to produce nutrients needed for plant growth and development. Organic fertilizer produced from this study have a pH ranging from 7.6 to 8.6. According to the regulation of the Minister of Agriculture No.70 / Permentan / SR.140 / 10/2011 the standard pH used in organic fertilizers ranges from 4 to 9 but at SNI: 19- 7030-2004 The standard pH used is 6.80 - 7.49.

Mature organic fertilizers have the characteristics of being scented such as soil, crumbs, blackish color, containing nutrients available to plants and high water-binding ability. Based on research that has been carried out the decomposition process occurred for three months, the organic fertilizer produced was blackish and smelled like soil. Organic fertilizer samples produced over three months have different textures depending on the organic fertilizer used. The fertilizers produced have different textures, colors, aromas and pH as shown in Figure 1.

![Figure 1. Resulted organic fertilizer/compost from agricultural waste](image)

In this study, the composition of L9 organic fertilizer samples used lamtoro, corn stover and chicken manure. Based on Figure 6, the L9 organic fertilizer sample decomposed well, the pH of this sample reached 8, with the texture of the L9 sample resembling soil, blackish and aromatic as the soil. The following results of organic fertilizer samples in terms of color, pH, aroma and texture can be seen in Table 1.

| Sample code | Compost color    | pH     |
|-------------|------------------|--------|
| L1          | Dark brownish    | 8.5    |
| L2          | Dark brownish    | 8.1    |
| L3          | Dark brownish    | 8.2    |
| L4          | Dark brownish    | 8.6    |
| L5          | Dark brownish    | 7.6    |
| L6          | Black            | 8.5    |
| L7          | Black            | 8.5    |
| L8          | Black            | 7.8    |
| L9          | Black            | 8.0    |
The composition of the sample of organic fertilizer used was straw, corn stover and goat manure. From the research that has been done, the organic fertilizer produced is blackish brown and smells like soil, but the texture that looks still looks rough and there are materials that have not been decomposed properly, this happens because the basic ingredients used such as straw are difficult to decompose because the straw contains lignin, one of the cells contained in plants that are like glue or cement that binds other cells in a single unit [24], [25]. The length of composting time is influenced by the content and nature of the material where the straw contains lignin making it difficult to decompose, the pH of L5 organic fertilizer reaches 7.6.

There are two kinds of color produced by organic fertilizer, namely in L1 - L5 samples, they are blackish brown and for black L6 - L9 samples the compost color changes occur based on the mixture of materials used, for the pH produced varies - from 7.6 to 8.6. Fertilizer samples containing cow dung (L1, L4 and L7) had a pH of 8.5 8.6 and 8.5 respectively. The increase in pH occurred because there was demineralization of micro elements Mg$^{2+}$, K$^+$, and Ca$^{2+}$. These cations will bind to the acids formed during the composting process and cause the composting reaction to increase in pH. Changes in pH are strongly influenced by the results of decomposition of cow manure biomass

3.2 Determination of P content
The calibration model was built to determine P content of organic fertilizers. It started from the raw spectrum and the corrected spectrum using the DT2, SNV and DT2+SNV methods. The purpose of doing the construction of the calibration model is to get the accuracy of the prediction model that is built based on statistical parameters and get information about the levels of phosphorus and potassium contained in organic matter. The PCR method works the same as a black box system where the way it works happens inside the software and is not visible so that the resulting model can be saved directly in the form of unsb files. The prediction performance for P determination using raw spectra data is presented in Figure 2.

![Prediction performance of P content using raw spectra data](image)

Figure 2. Prediction performance of P content using raw spectra data.

Obtained result shows that coefficient of determination of P content determination using raw spectra data is 0.6836 which is categorized as sufficient performance. The value of the correlation coefficient obtained from the results of prediction of raw data is equal to 0.82. The prediction of the raw data requires number of latent variable (LV) 7 which aims to increase the value of the correlation coefficient and reduce the root mean square error in calibration (RMSEC) value obtained. The RMSEC value obtained is 0.60. the robustness index or known as RPD value is also influenced by the standard
deviation of the actual measurement data, the resulting standard deviation for phosphorus is 1.16, so the resulting RPD value is 1.92 which is classified as a nearly good prediction. Descriptive statistics of actual measure P content of compost samples is shown in Table 2.

| Statistical indicators | value |
|------------------------|-------|
| Mean                   | 2.27  |
| Max                    | 4.00  |
| Min                    | 0.62  |
| Range                  | 3.38  |
| Standard Deviation     | 1.16  |
| Variance               | 1.35  |
| RMS                    | 2.53  |
| Skewness               | 0.23  |
| Kurtosis               | -1.19 |
| Median                 | 1.98  |
| Q1                     | 1.54  |
| Q3                     | 3.10  |

*Q1: first quartile, Q3: third quartile, RMS: root mean square*

The prediction results for P determination using DT2 correction method reduced the RMSEC value to 0.50 and enhance the value of the correlation coefficient, so that the value of RPD obtained was higher than raw spectra data. The results of prediction of phosphorus content using the DT 2 correction method is presented in Figure 3.

![Figure 3. Prediction performance of P content using DT2 spectra data.](image)

Based on obtained results, DT2 spectra corrections make the prediction performance is better to the overall results. This indicates that some important information on the spectrum is considered noise and is eliminated when the correction method algorithm is performed. Moreover, prediction models for P
content determination were also established using the SNV spectra correction, and lastly, we attempted to combine these both spectra corrections (DT2+SNV) to develop models used to determine phosphorus content in organic fertilizer samples. Prediction performance of SNV and combined DT2+SNV were presented in Figure 4 and Figure 5.

**Figure 4.** Prediction performance of P content using SNV spectra data.

**Figure 5.** Prediction performance of P content using combined DT2+SNV data.

Based on obtained prediction results, it show that the ability of the PCR method in terms of predicting levels of phosphorus content in organic fertilizers is classified as very good from the spectrum performed using DT2 and SNV corrections, but the resulting spectrum is still less dense and there is still contain noises using raw spectra data. In the DT2 and SNV methods the obtained spectrum results are closer and also the SNV successfully removes scatter effects from the spectrum and the correlation coefficient, the coefficient of determination increases to 0.71 and 0.70 respectively, the resulting RMSEC value decreases so that the value The RPD obtained increases to reach 2.4 for phosphorus prediction.
The highest prediction performance was achieved when the model is develop using a combination of DT2 + SNV. The correlation coefficient is 0.99, thus resulting RPD value 4.17 for phosphorus content prediction. Obtained results, also shows that the near infrared spectrum peaks and valleys are in the wavelength range of 1470.37 - 1600 nm and 1199.32 - 1222.19 nm where the wavelength shows that the absorption of the NIR spectrum in organic fertilizer is very high in terms of valley size and peak height so that it can predict the presence of phosphorus in organic fertilizer. The summary of the prediction performance for the phosphorus content determination in organic fertilizer samples is presented in Table 3.

| Spectrum       | Statistical indicators | R²   | r     | RMSE | RPD  |
|----------------|------------------------|------|-------|------|------|
| Raw            |                        | 0.68 | 0.82  | 0.60 | 1.92 |
| DT order 2     |                        | 0.71 | 0.84  | 0.50 | 2.34 |
| SNV            |                        | 0.70 | 0.84  | 0.52 | 2.21 |
| DT2+SNV        |                        | 0.98 | 0.99  | 0.28 | 4.18 |

Table 3. Prediction performance for P content determination using various NIR spectra data.

$r$: correlation coefficient, $R^2$: coefficient of determination, RMSE: root mean square error, RPD: ratio prediction to deviation, DT: de-trending, SNV: standard normal variate.

Near infrared which affects the material has little energy and only penetrates about one millimeter 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 [11]. 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 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 the sample or reflected.

4. Conclusion
The investigation study of utilizing agricultural waste onto organic fertilizers has been performed and phosphorus content of those fertilizer samples is determined using near infrared reflectance (NIRS). Achieved results showed that utilized compost has good characteristics according to standard regulation in the Ministry of Agriculture. It also concluded that NIRS was able to be used as an alternative method in determining P content of organic fertilizer samples with very good prediction performance.

Acknowledgment
We sincere acknowledge and would like express thank you to the directorate for research and community services (LPPM) Syiah Kuala University for funding support through research grant (PLK) scheme 2020.

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