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Predicting Nitrogen, Phosphorus, and Potassium Content in Dryland Agriculture Soils of Aceh Besar District Using NIRS Data Models

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ABSTRACT

This research aims to develop a Near Infrared Reflectance Spectroscopy (NIRS) model to determine the content of macro nutrients in dry agricultural land. The macro nutrient content is needed by plants to grow ideally. Every plant requires large amounts of macro nutrients such as nitrogen (N), phosphorus (P), and potassium (K). NIR spectrum data were collected from 30 samples in the range of 400-1100 nm using the Nicolet-Antaris device. The dual spectrum techniques used were Standard Normal Variate (SNV) and Mean Normalization (MN). This pre-treatment is chosen based on its function and aims to reduce or eliminate noise in the resulting spectrum. The corrected spectrum pattern helps to reduce discrepancies between spectral bands. The fewer gaps in the spectrum, the more accurate the resulting model. Next, the Partial Least Squares (PLS) and Principal Component Regression (PCR) algorithms are used to form a validation model. This multivariate analysis was carried out using the Unscrambler X 10.3 software. Model reliability is assessed using a number of statistical measures: correlation coefficient (r), coefficient of determination (R^2), root mean square error (RMSE) and range of error ratio (RER). The best model was taken based on previous findings when applying PCR to the MN-normalized spectra which was superior in predicting nitrogen and potassium content, while the Phosphorus content was superior when applying PCR with the SNV normalized spectrum technique. These findings show that NIRS combined with chemometric can be used to predict the nutritional content of nitrogen, Phosphorus and potassium quickly and simultaneously.

1. INTRODUCTION

Soil is a growing medium for plants, both annual and perennial plants. The soil body consists of 20-30% air, 20-30% water, 45% mineral material and 5% organic material [1]. Soil is formed by climate factors (i), topography (t), parent material (b), organisms (o), and time (w), which can be formulated T = f (I, o, b, t, w) [2, 3].

Soil as a medium for plant growth has characteristics that can be seen from its chemical and biological properties where the two interact to influence each other in the growth of a plant. Based on the forming factors, there are various types of soil in various locations. The type of soil will influence the level of soil fertility; thus the level of soil fertility varies in various locations [4].

Soil properties, which directly relate to the soil's role as a nutrient reservoir for plants, include both physicochemical and biological aspects. Soil physical properties include soil texture, soil structure, permeability and soil moisture. Chemical properties include ion exchange capacity, pH, base saturation, and aluminum saturation. Soil biology such as soil organic matter, N, P, K cycles, soil microorganisms [5].

Soil fertility is an important factor for plant survival and good production. Soil fertility is largely determined by the availability of nutrients that determine plant growth and production. Fertilization is very effective in meeting plant nutritional needs. Soil fertility factors are largely determined by the presence of nutrients in the soil, both macro nutrients, secondary nutrients and micro nutrients. Macro nutrients primarily include nitrogen (N), phosphorus (P), and potassium (K), while C, H, and O are basic elements also essential for plant growth. The nutrients N, P, and K are primary macro nutrients required by plants in quite large quantities, while the availability of these three nutrients in the soil is generally low. In general, higher contents of N, P, and K in the soil can increase soil fertility, thereby enhancing plant growth and yield [6].

Dry land is an expanse of land that is never inundated or only seasonally inundated with water [7]. Dry agricultural land generally has low levels of fertility, as well as low levels of organic matter too. This is further exacerbated by the limited use of organic fertilizer on agricultural land, especially on seasonal food crops [8].

The low level of soil fertility in dry land is also indicated by the organic matter content which is relatively low on average. Scientifically, the decline in soil organic matter levels in tropical areas is also relatively fast, it can reach 30 – 60% within 10 years. In fact, this organic material has a significant role in improving the chemical, physical and biological properties of soil. Even though the contribution of the macro nutrients N, P and K is relatively low, the role of organic matter is quite important, because it is a source of other essential nutrients such as C, Zn, Cu, Mo, Ca, Mg and Si [9].

Soil characteristics on dry land vary greatly depending on climate, soil type and agro-climatic zone. In this regard, solutions that can be taken to overcome the obstacles found on dry land include looking for alternative sources of water, using drought-resistant plants, managing effective and efficient irrigation systems, as well as improving the quality and level of soil fertility [10].

Plants can grow ideally if the necessary nutrient requirements are met. Each nutrient has a specific job and no single nutrient can replace it perfectly. One method that is often used to assess the fertility of soil is through an approach using soil analysis or laboratory tests. Laboratory analyzing requires a long duration, the cost of soil analysis is relatively expensive, and the availability of soil testing laboratories is limited. Currently, the technology that is being developed and has potential in precision agricultural practices is Near Infrared Reflectance Spectroscopy (NIRS). NIRS is a near infrared reflection technique that can be used to predict or detect nutrient content in soil. NIRS offers several advantages: it is a fast analytical method, requires relatively simple sample preparation, does not damage the material, operates without chemicals, and enables rapid and simultaneous predictions [11, 12].

NIRS technology works based on the principle that every biological material, including soil, has certain electromagnetic characteristics where the resulting spectrum can be analyzed to obtain information about the organic content of the soil, including predicting nutrient content as an indicator of the level of fertility and health of soil conditions. Infrared spectroscopy is a technique or method that uses near infrared (NIR) radiation to analyze the chemical composition of organic materials. This chemical content information is obtained based on the reaction of biological materials after being exposed to NIR radiation [13].

Each biological material has different optical characteristics and electromagnetic spectrum shapes, where the shape of this spectrum will characterize the chemical content of the material. This phenomenon has led many scientists to research the ability to apply this method to determine various qualities of organic materials such as fruit, soil, flour, animal feed and herbal leaves [13, 14].

The spectrum data obtained is then supplemented with chemometric analysis methods, making it possible to predict soil quality. Chemometrics is a statistical and mathematical method specifically for analyzing spectrum data which aims to reveal information and parameters of soil properties contained in the spectrum data [15].

Calibration is an initial measurement that regresses actual data with spectrum data. In previous research, a calibration model was constructed using 122 soil samples to predict levels of nitrogen, Phosphorus, and potassium. The best model employed the Principal Component Regression (PCR) method with Mean Normalization (MN) pretreatment. This model achieved correlation coefficients (r) of 0.99 and 0.93 for nitrogen and potassium, respectively, coefficients of determination (R^2) of 0.98 and 0.86, and residual predictive deviations (RPD) of 6.79 and 4.92. For predicting phosphorus levels, the Principal Component Regression (PCR) method with Standard Normal Variate (SNV) pretreatment was used, achieving a correlation coefficient (r) of 0.94, a coefficient of determination (R^2) of 0.88, and a residual predictive deviation (RPD) of 3.05. The best prediction model produced must be further quantified and evaluated through validation.

The validation process can be carried out if the previous process already has a calibration prediction model. In this research, validation was carried out on the previous calibration prediction model which aims to prove that using the best model produced during calibration is also able to predict nitrogen, Phosphorus and potassium levels in other samples used in the validation process. The best model resulting from validation will be used as a reference when testing nutrient levels in the field.

2. MATERIALS AND METHODS

2.1 Taking soil samples

In this study, the sample is collected from dry agricultural land in Aceh Besar Regency which was taken by purposive sampling (determining sample points) on a land use unit map based on land area. The method used is a type of observation method, namely direct sampling. Soil samples were taken using a soil drill. Soil samples were taken at a depth of 0-30 cm using a soil drill. The soil samples that have been taken are then put into containers that have been labeled based on the area where they were taken. Soil samples taken from the research location were then air-dried for a week, then the soil samples were crushed, sieved and ready for analysis. Analysis of nitrogen, Phosphorus and potassium content was measured using standard laboratory procedures using several equipment such as Atomic Absorption Flame Spectrometer (AAFS) and Atomic Fluorescence Spectrophotometry (AFS).

2.2 NIR spectra data acquisition

The near infrared spectrum for soil samples was acquired or obtained using an infrared spectroscopy instrument (Thermo Nicolet Antaris II) in the wavelength range used, 780 – 2500 nm with a workflow configuration built using the integrated software Thermo operation®. Workflow creation is carried out to organize tools for work. The NIRS tool settings are set with 32 scans, resolution 2.0 cm and gain 4x so that it can acquire the diffuse reflectance spectrum of the sample, then average the results, and save the scan results in two file formats namely *.SPA and *.CSV [16].

2.3 Building prediction models

The prediction model was built by regressing the NIR spectrum (variable X) with the nutrient content N, P, K from laboratory measurements (variable Y). The prediction model used is the model in previous research using the Principal Component Regression (PCR) and Partial Least Square (PLS) methods.

2.4 Model validation and evaluation

This stage is carried out to test the reliability and accuracy of the model being evaluated by reviewing its statistical parameters, namely: correlation coefficient (r), Root mean Square Error (RMSE), Range of Error Ratio (RER) and the number of Latent Variables (LV). Ideally a reliable model has high r and RER values and with a small number of LVs [17]. Predicted nitrogen (N), Phosphorus (P), and potassium (K) results were then compared with standard laboratory measurements and the best model was selected based on accuracy and reliability.

3. RESULTS AND DISCUSSIONS

3.1 Raw spectrum and spectrum correction

In NIRS, an object is irradiated with near infrared radiation and its reaction (reflection, absorption or transmission) is captured. As the radiation penetrates the object, its spectral characteristics change through wavelength-dependent scattering and absorption processes [17, 18]. In general, a typical diffuse reflectance spectrum in the infrared spectral range for a soil sample is shown in Figure 1. The data used to construct the soil spectrum was obtained during the spectrum acquisition process. The samples used were 30 soil samples.

Based on Figure 1, the raw spectrum shows the formation of slightly different peaks and valleys in the spectrum so that the peaks and valleys produced are not very clear. This is possible due to differences in chemical composition between nitrogen, phosphorus and potassium. Each different color indicates a different sample.

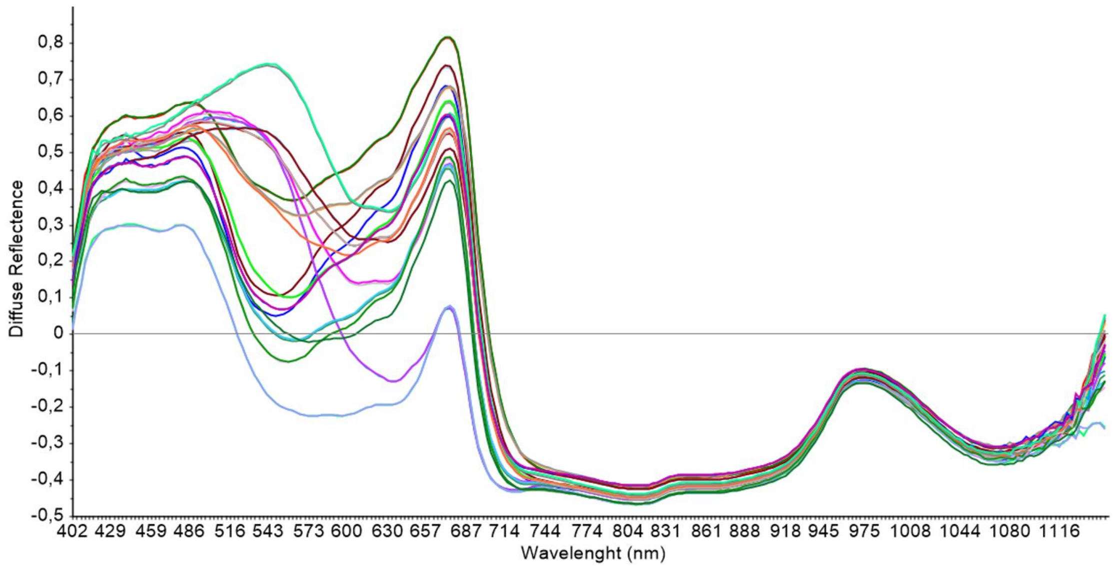

Figure 1. Raw soil spectrum

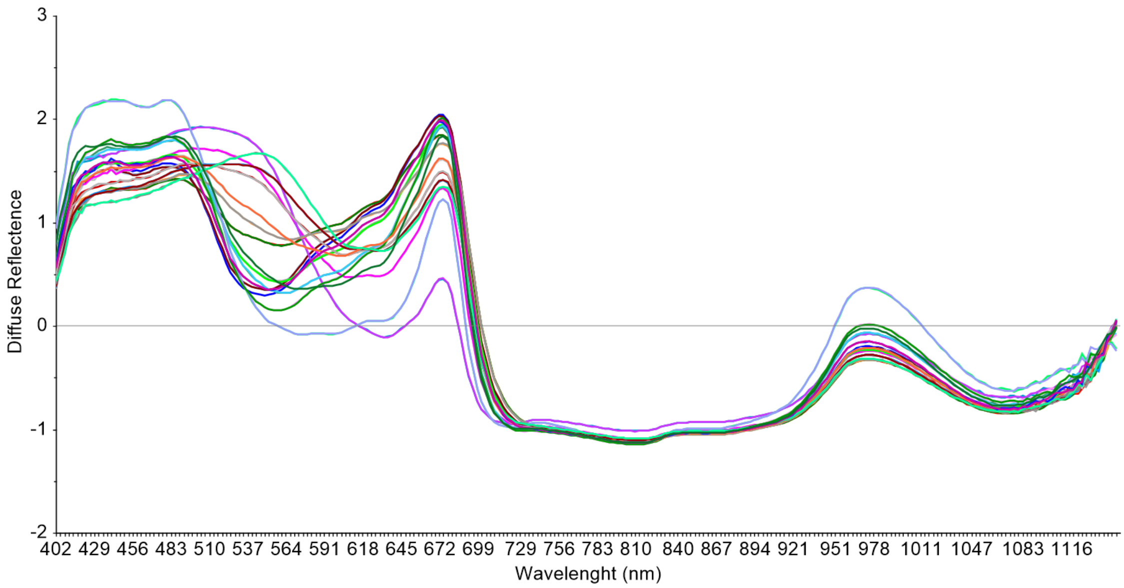

Figure 2. Soil spectra using SNV

Correction or pretreatment serves to reduce or eliminate noise in the resulting spectrum. The corrected spectrum pattern is able to reduce the stretch between the spectrum bands. In this study, Standard Normal Variate (SNV) and Mean Normalization (MN) pretreatment were used. Taking different pretreatments to find the most suitable combination for a specific soil analysis. SNV and MN pretreatment is generally used in soil analysis. SNV is a transformation used to eliminate scattering effects by centering and scaling each spectrum [19]. MN is a method that aims to scale the sample in order to obtain all data at approximately the same scale based on area, mean, medium, maximum, peak and unit vector [20].

The use of SNV pretreatment is useful for reducing noise in the spectrum so that the resulting spectrum is tighter and smoother. As shown in Figure 2, with SNV pretreatment the spectrum becomes tighter than the raw spectrum, this is because SNV is able to improve the spectrum that was originally tenuous.

In improving the spectrum by using MN, it produces a spectrum that is more tenuous than the raw spectrum. It can be seen in Figure 3 that the pattern in the MN spectrum is stretched which was originally tight. The valleys and peaks produced in the MN spectrum also become irregular.

Furthermore, the application of Mean Normalization pretreatment, where the corrected spectrum can be seen in Figure 3.

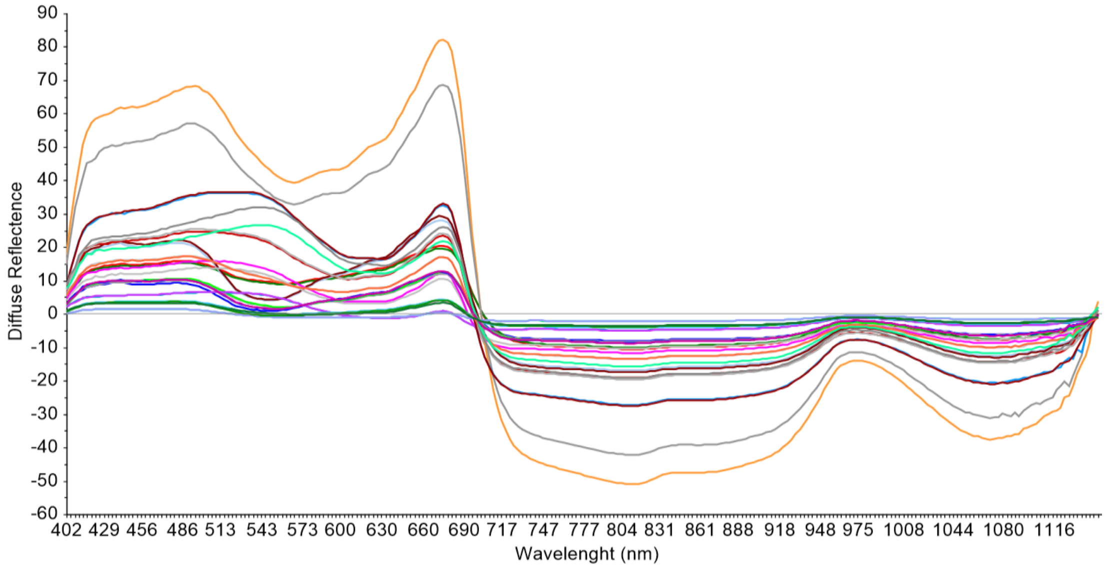

Figure 3. Soil spectrum using MN

3.2 Validation test of nitrogen, phosphorus and potassium levels in soil

Validation aims to test the reliability of the calibration model and ensure that the NIR calibration is good and can be used as a testing tool [21]. Validation is done after the calibration prediction model is obtained. The prediction model used is the best prediction result from previous research using the Principal Component Regression (PCR) method with Standard Normal Variate (SNV) and Mean Normalization (MN) spectrum improvement and the samples used are 122 soil samples. Based on the prediction data, a validation model is then built with the number of samples used, namely 30 soil samples. The methods used are Principal Component Regression (PCR) and Partial Least Square (PLS) methods with Standard Normal Variate (SNV) and Mean Normalization (MN) spectrum improvements. To calculate the resulting model, the descriptive statistical values of the soil samples must first be known as in Table 1.

Table 1. Descriptive statistics of actual measured quality parameters of soil samples

	Nitrogen (%)	Phosporous (mg/kg)	Potassium (cmol/kg)
Mean	0.30	31.02	1.68
Max	0.33	53.99	1.91
Min	0.24	18.99	1.28
Range	0.09	35.00	0.63
Std Deviation	0.03	9.13	0.20

Table 2 shows that the comparison of prediction values between the PLS and PCR methods is very different. Good predictions show low RMSE and high RER values. For the prediction of nitrogen levels using the PCR method in raw data, the prediction is still low with an RER value of 3.77, but after SNV pretreatment the RER value increases by 22.60 which is in the high prediction category but in MN pretreatment the resulting RER value is the same as raw data.

In the model validation test, the parameters considered are the correlation coefficient (r), the coefficient of determination (R^2), the root mean square error (RMSE) and the range of error ratio (RER). Good validation results can be seen from the largest R^2 value, low RMSE value, smallest latent variable (LV) and the largest RER value as in Table 2.

Prediction of nitrogen using PLS method with RER value on raw data of 7.79 which is included in the medium prediction, after SNV pretreatment the RER value increases to 15.07 including a very high prediction and on MN pretreatment the RER value drops by 3.77.

Phosphorus predicted using the PCR method with SNV pretreatment gets the best results compared to raw data and MN pretreatment, which is 26.78 in the high prediction category. Similarly, in the PLS method, the best RER value is also in SNV with an RER value of 39.15, which is with high prediction. So, it can be said that to predict phosphorus content, the PLS method with SNV pretreatment is superior to the PCR method both on raw data and using pretreatment.

Potassium prediction using PCR method obtained the best RER value using SNV pretreatment with a RER value of 8.13 using PLS method also obtained the best value using SNV pretreatment with a value of 6.75. PCR method with SNV pretreatment is superior in predicting potassium levels compared to PLS method both on raw data and using pretreatment.

The predicted values for N, P, and K indicate that the PCR method with SNV pretreatment excels in predicting nitrogen and potassium levels, while the PLS method with SNV pretreatment is most effective for phosphorus. Additionally, the RMSE values confirm that the PCR method with SNV yields lower errors for N and K, whereas it also provides a lower RMSE for phosphorus compared to the PLS method.

Table 2. Prediction results by comparing PCR and PLS methods

Soil Property	Regression Approach	Spectrum Correction Method	Statistical Indicators				
			Latent Variable (LV)	r	R^2	RMSE	RER
Nitrogen	PCR	*Raw* Data	1	0.144	0.020	0.024	3.77
		MN		0.088	0.007	0.024	3.77
		SNV		0.980	0.961	0.004	22.60
	PLS	*Raw* Data	1	0.882	0.778	0.011	7.79
		MN		0.086	0.007	0.024	3.77
		SNV		0.960	0.921	0.006	15.07
Phosphorus	PCR	*Raw* Data	1	0.149	0.022	8.878	3.94
		MN		0.100	0.010	8.934	3.92
		SNV		0.989	0.978	1.307	26.78
	PLS	*Raw* Data	1	0.979	0.960	1.787	19.58
		MN		0.260	0.067	8.67	4.04
		SNV		0.995	0.990	0.894	39.15
Potassium	PCR	*Raw* Data	1	0.366	0.134	0.18	3.53
		MN		0.231	0.053	0.189	3.36
		SNV		0.914	0.835	0.078	8.13
	PLS	*Raw* Data	1	0.752	0.565	0.128	4.96
		MN		0.055	0.003	0.194	3.27
		SNV		0.874	0.764	0.094	6.75

R^2: coefficient of determination, r: correlation coefficient, RMSE: the root mean square error, RER: range error ratio

3.3 Best performance of nitrogen, phosphorus and potassium levels

The coefficient of determination explains how much the ability of the independent variable (Vis-NIRS spectra data) to explain the variation in the dependent variable (reference data). The best performance for nitrogen and potassium levels using PCR method and SNV pretreatment and Phosphorus levels with PLS SNV can be seen in Figures 4-6.

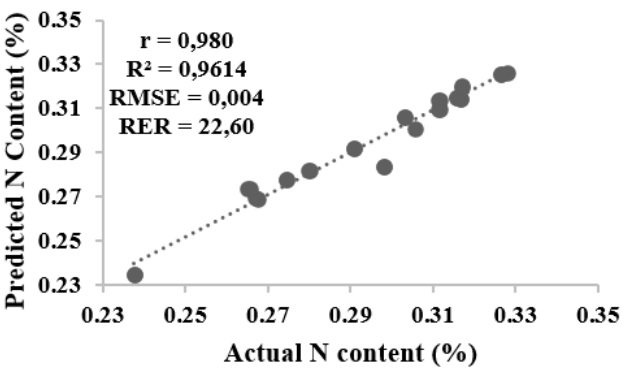

Figure 4. Performance of nitrogen levels with PCR SNV method

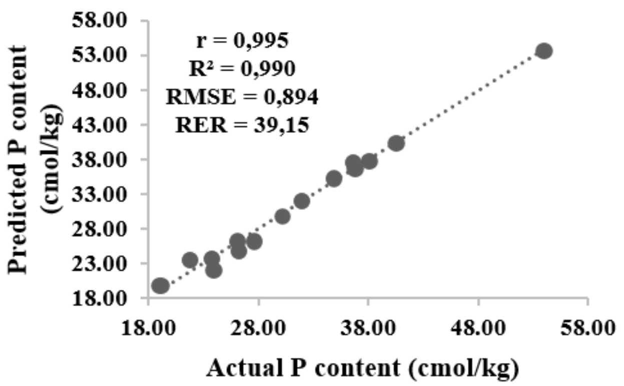

Figure 5. Performance of phosphorus levels with PLS SNV method

Figures 4-6 show different R^2 values, at nitrogen levels the R^2 value is 0.921 which is included in the excellent prediction category, at phosphorus levels the R^2 value obtained is 0.990 which is in the excellent prediction category and the R^2 value at potassium levels is 0.7649 which is included in quantitative prediction [22].

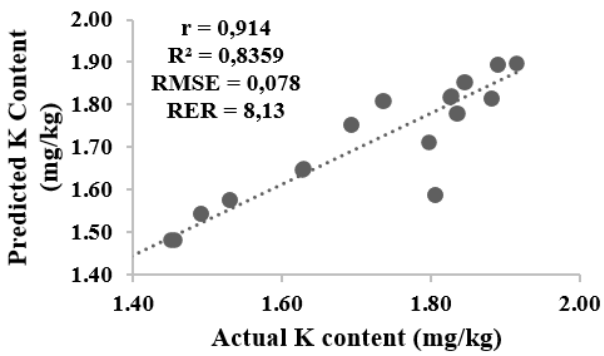

Figure 6. Performance of potassium levels with PLS SNV method

3.4 Prediction results for nitrogen, phosphorus and potassium levels

Prediction results of soil nitrogen, Phosphorus and potassium levels using 30 soil samples. The model was built using the Principal Component Regression (PCR) method with SNV pretreatment for nitrogen and potassium levels while for Phosphorus levels using the Partial Least Square (PLS) method with SNV pretreatment which can be seen in Table 3.

The best validation results were on nitrogen and potassium levels using Principal Component Regression (PCR) with SNV pretreatment with correlation coefficients (r) of 0.980 and 0.914 respectively, coefficient of determination (R^2) values of 0.961 and 0.835 respectively with RER -22.60 and 8.13 respectively. For phosphorus levels, the best results were using the Partial Least Square (PLS) method using SNV pretreatment with an r value of 0.995, an R2 value of 0.990 with an RER value of 39.15.

Table 3. Comparison of actual measurement values in the laboratory with predictions of nitrogen, phosphorus and potassium levels using near infrared spectroscopy

Spectrum	No.	Parameters					
		N		P		K	
		Actual	Prediction	Actual	Prediction	Actual	Prediction
	123	0.33	0.33	19.21	19.87	1.91	1.90
	124	0.31	0.31	21.76	23.59	1.74	1.81
	125	0.31	0.31	21.75	23.55	1.73	1.81
	126	0.33	0.33	19.03	19.91	1.89	1.89
	127	0.33	0.33	18.99	19.87	1.89	1.90
	128	0.27	0.27	40.40	40.39	1.46	1.48
	129	0.27	0.27	40.52	40.35	1.45	1.48
	130	0.32	0.32	23.68	23.77	1.83	1.82
	131	0.32	0.32	23.69	23.79	1.83	1.82
	132	0.24	0.24	53.94	53.65	1.28	1.23
	133	0.24	0.24	53.99	53.65	1.28	1.23
	134	0.31	0.31	27.62	26.39	1.84	1.78
	135	0.31	0.31	27.60	26.28	1.83	1.78
	136	0.28	0.28	34.85	35.33	1.53	1.58
Standard Normal Variate (SNV)	137	0.28	0.28	34.80	35.29	1.53	1.58
	138	0.30	0.31	26.06	26.35	1.69	1.75
	139	0.30	0.31	26.03	26.29	1.69	1.76
	140	0.30	0.28	36.62	37.58	1.81	1.59
	141	0.30	0.28	36.60	37.56	1.81	1.59
	142	0.32	0.31	26.17	24.85	1.88	1.82
	143	0.32	0.31	26.17	24.84	1.88	1.82
	144	0.27	0.28	36.76	36.78	1.49	1.54
	145	0.27	0.28	36.74	36.76	1.49	1.54
	146	0.29	0.29	31.96	32.11	1.63	1.65
	147	0.29	0.29	31.87	32.03	1.63	1.65
	148	0.27	0.27	37.98	37.89	1.39	1.52
	149	0.27	0.27	38.10	37.88	1.38	1.52
	150	0.32	0.32	23.92	22.22	1.84	1.85
	151	0.32	0.32	23.80	22.10	1.85	1.86
	152	0.31	0.30	30.10	29.82	1.80	1.71

3.5 Loading plot of nitrogen, phosphorus and potassium levels

Based on the results of the NIRS spectrum prediction model in dryland soils of Aceh Besar Regency, it can predict nitrogen, Phosphorus and potassium levels using 3 types of agricultural dryland soils. The Loading Plot obtained can determine the relevant wavelengths that can predict the levels of nitrogen, Phosphorus and potassium in the soil. According to study [23], the presence of peaks and valleys in the NIR spectra is due to the influence of the chemical content in a material.

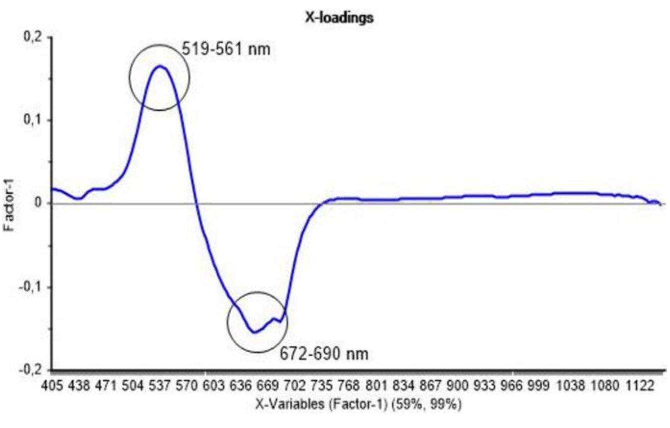

Figure 7. Loading plot for nitrogen, phosphorus and potassium

Figure 7 shows the peaks and valleys of the NIRS spectra at wavelengths of 519-561 nm and 672-690 nm for nitrogen, phosphorus and potassium levels in drylands of Aceh Besar District. Nitrogen levels are formed from N-H molecular bonds, phosphorus levels are formed from P-O bonds, where O refers to O-H bonds. Similar to phosphorus, potassium is also formed from K-O bonds, where O is formed from O-H. The response of the molecular bonds forming the nitrogen, Phosphorus and potassium levels provides information through the sign of the spectrum pattern regarding the organic bonds of the molecules so that the main chemical constituents of the object can be determined.

4. CONCLUSIONS

This research concludes that there is a significant difference between PCR method and PLS method. Proven by the validation results of nitrogen and potassium levels using the PCR method with SNV pretreatment, the coefficient of R2 values were 0.961 and 0.835 respectively with RER values of 22.60 and 8.13 respectively. For phosphorus levels using the PLS SNV method, the coefficient of R^2 was 0.990 with a RER of 39.15. The best validation results for nitrogen and potassium levels use PCR method with SNV pretreatment, while for Phosphorus levels use PLS method with SNV pretreatment.

NIRS technology has a big impact on the field of soil analysis because this technology is able to predict nitrogen, Phosphorus and potassium levels quickly, effectively and efficiently and is environmentally friendly because it does not involve the use of chemicals in its application and does not damage the material. It is suggested that for future research include testing Nitrigen, Phosphorus and potassium levels in other dry agricultural land than Aceh Besar Regency.

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