Integrating Spectroscopy in the Land Resources Monitoring to Support Agricultural Nutrient Management in Indonesia

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ABSTRACT

Spectroscopy studies material responses to the incident electromagnetic radiation. This method has been proven to be cost-effective for either soil or plant nutrient analysis. Furthermore, it offers rapid and high throughput quantitative data measurement with non-destructive, waste-free and minimal sample preparation processes. This article reviews potential use of spectroscopy technology in land resources monitoring as the cost-effective solution, particularly in the developing nations where natural resources monitoring might not be part of national development priority. The discussion is focused on the use of visual/near-infrared spectroscopy (VNIRS) for soil nutrients prediction, particularly to support cropland nutrient management of three main food crops in Indonesia, i.e. paddy, maize, and soybean.

Keywords: Land resources monitoring, soil-nutrient management, VNIRS

ABSTRAK

Spektroskopi mempelajari respon materi terhadap radiasi elektromagnetik yang terjadi. Metode ini telah terbukti efektif dari segi biaya untuk analisis nutrisi tanah atau tanaman. Selain itu, Teknik spektroskopi menawarkan pengukuran data kuantitatif yang cepat berpresisi tinggi dengan tanpa merusak sampel, bebas limbah, dan presiapan sampel minimal. Artikel ini mengulas potensi penggunaan teknologi spektroskopi dalam pemantauan sumber daya lahan sebagai solusi yang hemat biaya, terutama di negara-negara berkembang di mana pemantauan sumber daya alam mungkin bukan merupakan prioritas pembangunan nasional. Diskusi difokuskan pada penggunaan spektroskopi pada pita visual/inframerah-dekat (VNIRS) untuk prediksi nutrisi tanah, terutama untuk mendukung pengelolaan nutrisi lahan pertanian dari tiga tanaman pangan utama di Indonesia, yaitu padi, jagung, dan kedelai.

Kata kunci: Monitoring sumber daya lahan, management nutrisi-tanah, VNIRS

BACKGROUND

Anthropogenic pressure on the ecosystem services is increased with the global population growth, which is expected to reach 9.7 billion people by 2050 (Cohen, 2003; United Nations, 2015). But since the population increase is not balanced with the extension of the arable land, the ratio of the cultivated land per person is decreasing overtimes, with global average at 0.2 ha/persons in 2014, which was 13% decrease from 2000 (World Bank, 2014). This ratio is particularly lower in the developing nations where high population increases are expected to occur, i.e. 0.18 ha/person in an average of non-high-income countries, compared to 0.30 ha/person in high-income countries. As the land to people ratio receding, agricultural land has been intensified to fulfill the increasing human needs for food in the past decades. However, mismanagement on land uses has been degrading land quality that even lowering its productivity. For example, the application of inorganic fertilizer, which is usually coupled with pesticide, is a common practice to enhance crop productions. But misapplication due to less information on the status of the soil properties might lead to over-fertilization that not only does not contribute to the plant growth but also increasing pollution to the surrounding ecosystem (Brady and Weil, 2008). Furthermore, not only mismanagement in land use practices, this condition is also worsened by the global climate change that increases the probability of crop failure, due to the increasing frequency of flood or prolonged drought periods. Therefore, the challenge to the land managers is increased on how to sustain food production while maintaining the quality of the land resources in the changing environment.

Resource information is the key to management before application of certain strategies. In term of crops production, therefore, quantitative understanding of the status of the soil properties and plant nutrients are needed before particular land management scenarios are going to be applied at any locations. Soil and plant nutrients can be monitored at best precision through traditional sampling and laboratory analysis, but these practices are resource demanding in term of money, time, and workload (Foley et al., 1998; van Maarschalkerweerd and Husted, 2015); hence, feasible only at the smaller scale of observation. Furthermore, some of the laboratory procedures even produce wastes that later might be endangering the ecosystem. At the other hand, qualitative monitoring, such as leaf color observation to identify plant diseases and nutrient deficiencies, although simple and low cost but only gives vague results that later cannot be used as the quantitative basis for resource use efficiency. A quantitative cost-effective method for land resources monitoring is therefore needed to support continuous and extensive land resources management. This review is intended to address this issue by proposing spectroscopy method as the cost-effective solution for soil and plant monitoring to support land resources management, particularly in the developing nations where natural resources monitoring might not be the part of the development program priority. The discussion is going to be focused on the use of visual/near-infrared spectroscopy (VNIRS) for soil nutrients prediction, particularly to support cropland nutrient management of three main food crops in Indonesia, i.e. paddy, maize, and soybean.

Spectroscopy Application in Soil and Plant Nutrients Analysis

Spectroscopy studies material responses to the incident electromagnetic radiation. This method, especially the lower energy (less than 3.1 eV) spectroscopy that includes visible up to near-infrared region (VNIR), has been proven to be cost-effective for either soil or plant nutrient analysis, and offers rapid and high throughput quantitative data measurement with non-destructive, waste-free and minimal sample preparation processes (Foley et al., 1998; Lee et al., 2010; Shepherd and Walsh, 2007; Viscarra-Rossel et al., 2006). Furthermore, recent advances in spectroscopy also open the possibility to perform in-situ VNIR spectral measurements, which result in comparable outcomes with laboratory-based spectroscopy analysis (Viscarra-Rossel et al., 2009). The reflectance electromagnetic spectrum within this wavelength region shows spectral signature for different molecules due to asymmetric vibration of the molecular bond, which is caused by molecular stretching and/or bending, that absorbs incident light at the range of its vibration frequency (Foley et al., 1998; Stenberg et al., 2010). The resulted reflectance/absorbance spectrum is, therefore, an indirect measurement of the material properties containing spectrally active molecules, which later needs to be calibrated with the known composition sample (Stenberg et al., 2010; van Maarschalkerweerd and Husted, 2015). Furthermore, content or properties that are related to other spectrally non-active molecules might also be retrieved by observing its correlation with the properties of the spectrally active molecules (Brown et al., 2006; Idowu et al., 2008). Table 1 summarizes spectral signature of several known compounds with its related properties in the range of VNIR wavelength (Stenberg et al., 2010; Viscarra-Rossel et al., 2009).

Table 1. Spectral signature at VNIR region of several known compounds

Properties	Molecular bonds	Wavelength (nm)
Iron oxide	$\alpha - FeOOH, \alpha - Fe_2O_3$	400-600 and 750-1100
Nitrogen	$N - H$ (Amine)	1500, 1000, 751
Polysaccharides	$C - O$	2137
Aromatics	$C - H$	1650, 1100, 825
Combination vibration of water	$O - H$	1850-2100
Combination vibration of minerals	$Fe - OH,\ Mg - OH, Al - OH$	2100-2400

Spectroscopy has been applied in the quantitative nutrient monitoring of soil and plant with various degree of precision. This technique has been more broadly applied in soil than in plant monitoring due to its practicability, cost efficiency, and result stability (van Maarschalkerweerd and Husted, 2015). In agriculture, crop nutrients availability can be measured with spectroscopy directly at the plant tissues or through soil. While plant spectroscopy analysis might give instant reading about plant nutrient availability, this method might be less practical since it is not only influenced by the individual properties of the crop species, such as the crop cultivar or the individual crop health (related to pest and diseases), it is also time and site-specific, and therefore, varies depending on the multiple parameters such as the growing stage, season, soil quality, and the sample conditions (Stenberg et al., 2010). Soil spectral measurement at the other hand can be performed with the more stable sample at a more flexible time (before, during, or after the growing season). Compare to plant, the soil has less variability and more resistance to changes so that the sample represents the larger area and its analysis result might still valid for longer time periods. Therefore, soil spectroscopy is more effective and efficient for agricultural management planning. For nutrient management, the pattern of the soil nutrient status can be monitored periodically at specific times during the growing period, and the result, together with the recorded amount of soil amendment inputs, can then be correlated with the crop productions, to define fertilizer recommendation. Furthermore, plant spectroscopy might be utilized to confirm the results this recommendation.

Published literature have shown that several properties of the soil and plant have been successfully predicted from its spectral pattern. In the region of VNIR (400 - 2500 nm), soil organic carbon is the soil property with relatively high predictability, with adjusted coefficient of correlation on validation (r^2) higher than 0.85 (Chang et al., 2001; He et al., 2007; Vasques et al., 2010, 2009, 2008). The soil organic carbon is highly predictable by spectroscopy method since the structure of the soil organic carbon is mainly composed of O-H, C-O, and C-H bonding that are spectrally active in the near infrared region. Furthermore, among the soil macronutrients, which the information is used for fertilizer recommendation, only soil available nitrogen (N) is having high predictability, with r^2 for N and either of phosphorus (P) or potassium (K) are in the range of more and lower than 0.85 respectively (Chang et al., 2001; He et al., 2007). High predictability of soil N is due to strong spectral signature of amide (C-N) and/or amine (N-H) bonding and also its correlation to SOM content (Stenberg et al., 2010). Nevertheless, the N concentration in soil is also generally much higher than either P or K, which is in the order of g/kg and mg/kg, respectively; hence, having better signal to noise ratio. At the sites where soil P concentration is higher, however, the predictability of the soil available P is improved with r^2 more than 0,85 (Bogrekci and Lee, 2005). Other soil properties that are discernable in the range of VNIR wavelength include: soil color and mineral composition, including iron oxides (Haematite, Goethite), clays (ex. Smectite, Kaolinite, Attapulgite), and carbonates; soil structure, which is derived from clay content; other soil nutrients, such as Calcium (Ca), Iron (Fe), Magnesium (Mg), and Manganese (Mn); soil cation exchange capacity (CEC); and soil water content, including soil moisture and 1.5 MPa water (Chang et al., 2001; Viscarra-Rossel et al., 2009). Further soil spectral observation in the mid-infrared (MIR) region shows up to 10% improvement of the coefficient of correlation on the calibration model generated by VNIRS, particularly for soil organic carbon and organic matter content (Knox et al., 2015; Viscarra-Rossel et al., 2006). This result is mainly caused by stronger fundamental vibration for organic matter molecules at the MIR region, compared to its weaker overtones that is observable at the VNIR region (Foley et al., 1998; Knox et al., 2015; Stenberg et al., 2010; Viscarra-Rossel et al., 2006). However, for mass application of land resources monitoring, it is worth noticing that the improvement from MIR spectroscopy analysis is achieved by trading off the ease of use of VNIRS that offers more rapid measurements, simple sample preparation, low cost of the instrumentation, and also the possibility of in-situ measurement (Viscarra-Rossel et al., 2006).

VNIRS is vastly used to measure plant chlorophyll, from in-situ measurement up to satellite-based remote sensing. The reflectance value at Red (R_{RED}) and NIR (R_{NIR}) regions are used to construct formula to calculate the normalized difference vegetation index ($NDVI = \frac{R_{NIR}-R_{RED}}{R_{NIR}+R_{RED}}$). Leaf with higher chlorophyll content absorbs incident light at the Red region; hence, result in low reflectance, yielding NDVI value close to 1 (van Maarschalkerweerd and Husted, 2015). Two plant minerals related to chlorophyll content that can be predicted using VNIRS are N and Mg. Other detectable organic compounds include lipids and ester, which is related to organic P content (van Maarschalkerweerd and Husted, 2015), and also phenolic and lignin (Foley et al., 1998). Furthermore, for grass type plants, the VNIRS calibrations yield relatively high prediction performance models for the plant macronutrient analysis (including N, P, K, Mg, and Ca), but lower performance for the micronutrients (including Fe, Mn, Zn, and Cu), with average r^2 more and lower than 0.8 respectively (de Aldana et al., 1995; Huang et al., 2009; Ward et al., 2011). The low predictability of the plant micronutrients contents might be due to its lower concentration in the plant tissues, such that its variability is overshadowed by the spectrum noises.

Agricultural Profile and Challenges in Indonesia

Indonesia is an archipelagic country with about 2/3 of its territorial area is the ocean. It is located on the equator at about 120^{o} longitude, with the total land area is about 181.2 million hectares. Its ratio of the arable area to the total land area increased from about 10% at 1961 to 13% at 2014, but it is imbalance with the population increasing rate, as Indonesia population increased from about 88 million to 254.5 million at the same period; therefore, reducing the arable land to population ratio from 0.20 to 0.09 ha/person (World Bank, 2014). As the result, food demand increased and croplands then were intensified, especially for the three main food crop commodities in Indonesia, i.e. paddy, maize, and soybean. The intensification was indicated by the increasing area of the irrigated agricultural lands, from about 130,000 to 530,000 hectares in the period of 2008-2012 (Indonesia Directorate General of Agricultural Infrastructure and Facilities, 2012), and the increasing of the total fertilizer input per hectare of land, including Urea, Ammonium, Phosphate, NPK, and organic fertilizer, from about 390 to 500 kg/ha (national average) in the period of 2007-2014, with increasing rate at about 15 kg/ha/year (Indonesia Center for Agricultural Data and Information, 2014; Indonesia Directorate General of Agricultural Infrastructure and Facilities, 2012; Indonesia Fertilizer Producers Association, 2017). Furthermore, although highly variable, the fertilizer consumption to produce one ton of food also shows increasing trend, at about 1 kg/ton/year. This trend not only becoming one of the possible cause of the food price increases, but can also have two possible meaning, which is either (1) inefficient fertilizer application, which increasing the risk of ecosystem pollution, and/or (2) the sign of soil degradation, in which more soil amendment is required to stabilize its productivity. Inefficiency in fertilizer application might relatively easy to be fixed by gradually reducing the fertilizer consumptions. But this inefficiency needs to be assessed before such reduction is going to be implemented since this might have a negative impact on the national food security. Furthermore, if the soil has been degraded, conservative land management strategies need to be implemented to regain the soil health, but this also requires intensive and integrated land resources assessment. Traditional laboratory analysis methods, which have been done for the past decades, might produce higher precision data as the basis for the assessment, but only covers plot at the smaller scales of analysis and were not be able to be conducted periodically due to its expensive costs; therefore, it is not suitable for regular monitoring at the national scale. VNIRS, at the other hand, although might be less accurate compared to the laboratory analysis, offers high throughput data with simpler analysis (Viscarra-Rossel et al., 2009), and therefore is a potential method as the cost-effective solution for continuous land resources assessment at the national scale to support agricultural nutrient management.

[a] The rate is the slope of the linear regression line of the annual ratio of the fertilizer consumption per hectare of the cropland ($r^2 = 0.74$). This ratio was calculated by multiplying the ratio of the annual total fertilizer consumption to the food crops production with the annual average of croplands productivity (paddy and maize only).
[b] This is rough approximation ($r^2 = 0.2$), and cannot be referred as the exact number of the ratio of the fertilizer requirements per ton of food crop production. This number was calculated based on the total annual production of paddy and maize only, which represent more than 90% of the total domestic production of food crops in Indonesia.

Methodological Implementation of VNIRS for Agricultural Land Resources Monitoring

In the agricultural field, the main goal of nutrient management is to efficiently use soil amendments for maintaining soil quality to enhance land productivity (Brady and Weil, 2008). Nutrient requirements can be determined by interpreting the status of the soil properties and observing the pattern of the nutrient balance over the growing periods. As an indirect method, VNIRS calibration model needs to be developed before it can be integrated into spatial and temporal soil monitoring processes (Stenberg et al., 2010). This model is developed based on the known sample properties, to predict soil status as a function of the soil spectrum wavelengths. Therefore, three steps to implement VNIRS for nutrient management in the agricultural land include (1) soil spectral database development, (2) calibration model development, and (3) VNIRS implementation for soil monitoring.

Soil Properties and Spectral Database Development

The soil spectral database consists of two soil dataset that includes the soil spectral data (predictor) and the soil properties data (predicted). For model development, soil spectrum is measured both at the laboratory and the location (in situ). The differences between these two measurements need to be approximated since soil monitoring is going to be performed in situ using model that is developed in the laboratory. The use of laboratory spectral measurement in the model development is preferable since it generally has a better signal to noise ratio. Furthermore, the predicted parameters for soil nutrient management include not only soil macro and micronutrients status, but also soil properties for soil characterization that includes organic matter (carbon), mineralogy, and clay content (Brown et al., 2006). During this phase, however, the cost of the analysis is higher compared to the traditional soil analysis, due to the additional spectral parameter measurements. But in the long run, this cost will be significantly reduced, since the laboratory analysis will be unnecessary.

To model the broad variation of the soil information at the national scale, sample variations needs to represent all of the population (Foley et al., 1998). But, the number of the sample included needs to be limited so that the database development is cost effective. Therefore, two strategies are available for database development, including (1) utilization of freely available global soil spectral library, and (2) the development of new Indonesia spectral library. The first strategy is the most cost-effective method that can be implemented during the initial stage of the VNIRS application. A global spectral library that contains 785 soil profiles with 102 unique locations from Indonesia (soil sampling period 1980-1992) is available for free download at the International Soil Reference and Information Centre (ISRIC) websites (International Council for Research in Agroforestry, 2013). However, this dataset might yield calibration model with low prediction performance considering the lower number of the available samples and the data year that might not represent current soil condition. Further improvement can be expected by spiking this dataset with new representative soil samples. This technique, therefore, might yield model with considerable prediction performance, while maintaining the lower cost of the required analysis.

The second strategy is the ideal method for VNIRS application and is expected to yield calibration model with the best prediction performance. But this method is resource demanding due to intensive traditional laboratory analysis requirements. Soil sampling strategy is therefore required to reduce the cost of the analysis. Stratified random sampling is one of the sampling strategies. Using this technique, Indonesia region can be classified into map units using Geographical Information System (GIS) technique, based on the soil forming factors that are relatively stable over longer time periods (longer than human periods), from which random samples can then be collected. These factors include the soil classification information (ex. soil taxonomy), topographic properties (ex. altitude, slope, landform), ecological characteristics (ex. climatic zone, historical land use), and parent materials (Grunwald et al., 2011). For Indonesia region, this factors can be retrieved either from the freely available global dataset (Ellis et al., 2010; Hartmann and Moosdorf, 2012; Hengl et al., 2016; Jarvis et al., 2008; Kottek et al., 2006), or from the available national geospatial dataset from the past land monitoring projects (Indonesia soil, topographic, climate, land use, and geologic maps).

Calibration Model Development

Two steps on the calibration model development include data preprocessing and chemometrics. Data preprocessing is performed mainly to improve the data quality so that it is more interpretable, but without changing the original data structure (Wehrens, 2011). Basic data preprocessing, such as data transformation, centering, scaling, and normalization, can be applied to soil properties data, but more advanced techniques need to be performed to dealing with soil spectral data (Varmuza and Filzmoser, 2009). Example problem with VNIRS data includes spectrum noises due to instrument reading limitation and/or spectral offset that is caused by scattering effect (Wehrens, 2011). Furthermore, common techniques for spectral data smoothing and offsetting include the running mean/median, Savitzky-Golay filter, first and second derivatives calculation, continuum removal technique, and/or combination of these techniques (Savitzky and Golay, 1964; Varmuza and Filzmoser, 2009; Viscarra-Rossel et al., 2009; Wehrens, 2011). The application of data preprocessing before calibration processes has been proven to improve the resulted model prediction performance (Vasques et al., 2008). An important aspect of chemometrics is the application of statistical multivariate data analysis for chemistry-related problem solving (Varmuza and Filzmoser, 2009). Therefore, multivariate data analysis is used to identify the type of molecular bond from a series of soil spectrum measurement, so that the status of the related soil properties can then be quantified. Some popular methods that have been proven to yield calibration model with relatively high prediction performance include partial least square regression (PLSR) (Knox et al., 2015; Vasques et al., 2010, 2009, 2008; Viscarra-Rossel et al., 2009, 2006), principle component regression (PCR) (Chang et al., 2001), regression tree (Brown et al., 2006), and random forest (Knox et al., 2015). Furthermore, for VNIRS, Savitzsky-Golay derivatives and PLSR are considered to be a combination of data preprocessing and multivariate technique that yields relatively high and stable prediction performance (Vasques et al., 2008), hence, are the candidate for calibration model development.

VNIRS Implementation Strategy for Agricultural Land Resources Monitoring in Indonesia

Two different approaches are proposed for VNIRS implementation. The soil database and spectral library are developed using a centralized system to simplify the data management and model development processes. Therefore, data and the calibration model are disseminated to the land managers through a top-down approach. The soil monitoring processes, at the other hand, are applied in a distributed manner, using a bottom-up approach. Sampling is performed by the land managers, where the data is then uploaded into the database. Implementation of in situ measurements, to reveal the status of particular soil properties at specific times (ex. before and/or after fertilizer application during the crop growing period), which is equipped with a geographical positioning system (GPS), are preferred whenever the cost of the implementation is reasonable. This method directly connects the central database to the farmer fields, so that land managers can then use the model directly to guide in the nutrient management, while at the same time scanning the samples where the data are automatically uploaded to the central database. Alternatively, if the cost of the instrumentation is too high, a secondary spectroscopy laboratory network can be developed at the provincial level, which serves as a bridge between the central database and the land managers. Soil samples are collected by land managers and sent to this laboratory, where data samples are processed, uploaded, and interpreted; and the results are sent back to the land managers. This alternative method might introduce delays, due to additional time to send, process the samples, and disseminate the results; but significantly reduces the implementation cost. Furthermore, the implementation of this monitoring system should follow the existing agricultural institutional network. Currently, there is about 25,000 agricultural extension personnel that potentially become the land managers (Indonesia Ministry of Agriculture, 2016). This personnel are distributed over 34 provinces and have the advantage of having a direct relation to the local farmers.

Another important aspect in VNIRS implementation for agricultural land resources assessment is the identification of representative locations for periodical soil monitoring. This location should be located in the area with similar soil forming factors and land managements. For nutrient management of the annual crops, this observation is particularly important to understand the nutrient balance over the growing period and its relationship with the land productivity. Furthermore, continuous soil monitoring at the same representative locations also opens the possibility to extend the analysis for agricultural decision support system at the national scale.

CONCLUSION

Spectroscopy, especially VNIRS, has been proven to be a cost-effective method for soil status monitoring. Particularly in the agricultural field, this method offers continuous and in situ observation of nutrient balance as an important information for land management; therefore, is potential to be integrated into agricultural land resources assessment in Indonesia. As an indirect method, VNIRS requires calibration model to be developed before its implementation. Furthermore, this model development requires the support from representative samples that covers overall population variations. The resulted calibration model should then be disseminated to and used by the land managers to generate information about soil property status over particular growing time period, and then to guide the croplands nutrient management.

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