Hyperspectral Sensing to Estimate Soil Nitrogen and Reduce Soil Sampling Intensity

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1.1 Abstract

Optimal crop management relies on accurate measurements of soil nitrogen and a comprehensive understanding of its spatial variability. However, spatially characterized information on soil nitrate-nitrogen (NO_3-N) is not always readily available during fertilizer application practices. The complex mobility of soil NO_3-N, coupled with the labor requirements and high costs linked to soil chemical analysis, underscores the necessity for an alternative method. An improved approach is warranted to achieve precise soil NO_3-N estimation, ensuring it remains cost-effective and straightforward. In this study, non-imaging hyperspectral sensor with *visible to short*-wave infrared spectrum were used to estimate soil NO_3-N content. The objective of this study was to estimate surface soil NO_3-N using non-imaging hyperspectral sensing. Soil samples were analyzed for soil NO_3-N and spectral measurements were acquired with ASD FieldSpec3 spectroradiometer. Spectral preprocessing techniques were applied to refine the spectral data and remove noise. Effective spectral windows were determined such that spectral demonstrated sensitivity to changes in soil NO_3-N. The selected spectral windows: W1 (1460-1690 nm), W2 (1730-1780 nm), and W3 (1940-2150 nm) were used to estimate soil NO_3-N. Partial Least Squares Regression (PLSR) and Random Forest Regression (RFR) were used to estimate soil NO_3-N using selected spectral features and measured soil NO_3-N. Estimated soil NO_3-N map were developed. Map of measured soil NO_3-N showed a similar spatial trend estimated with estimated soil NO_3-N

maps. The findings of potential of hyperspectral data-based soil NO_3-N estimation models provide a cost-effective and practical technique to improve soil fertility management practices.

Introduction

The conventional soil sampling and laboratory-based routine chemical analysis to determine soil nitrogen are labor-intensive, expensive, and time-consuming (Janik et al., 1998). Furthermore, they typically necessitate the utilization of hazardous chemicals, such as concentrated acids and alkalis, which introduce potential safety hazards. Therefore, assessing soil nitrogen status needs an indirect technique that is capable of reducing soil sampling intensity to make it less labor intensive, as well as cheaper, quicker, non-destructive, and chemical free. Many researchers have used multiple tools including electrochemical sensors and optical techniques (spectroscopy) to rapidly, inexpensively, and indirectly estimate soil nitrogen (Adamchuk et al., 2004). In recent times, reflectance spectroscopy is being used to quantify soil nitrogen (Vibhute et al., 2020a; Vohland et al., 2014; Xiao et al., 2018). These techniques offer numerous advantages over traditional methods, including non-destructive sample analysis, cost-efficiency, user-friendliness, and rapid processing of large sample volumes with minimal sample preparation (Demattê et al., 2004). This study undertakes the challenge of estimating soil nitrogen while reducing soil sampling intensity, leveraging spectral similarities through application of the hyperspectral sensing tool. The objective of this study was to estimate surface soil NO_3-N using non-imaging hyperspectral sensing.

Materials and Methods

This study was conducted over two years (2021 and 2022) across three study locations in the state of Kansas. Soil samples were collected from all three site years. Within field soil sampling locations were identified with a stratified random soil sampling design. A composite soil sample consisting of multiple soil cores was collected per 0.202 ha grid cell size for each study area. Spectral measurements were acquired for the soil samples at the Precision Ag Lab, Kansas State University, using a FieldSpec3 spectroradiometer (Analytical Spectral Devices, Boulder, CO, USA). The ASD FieldSpec3 has a spectral range from 350 nm to 2500 nm. The spectral reading was measured for soil samples following the protocol suggested by the Soil Spectroscopy Group and the Development of a Global Soil Spectral Library (Viscarra Rossel et al., 2006). The spectral pre-processing techniques applied were objective oriented and case sensitive. Splice correction, removal of reflectance below 40 nm, Savitzky–Golay smoothing, Multiplicative scatter correction (MSC) and continuum removal were applied to minimize the influence of noise, remove spectral artifacts, and enhance the signals present in the dataset. Experiments were conducted in this study to select effective spectral windows that are sensitive to Nitrate-nitrogen. The Spectral Angle Mapper (SAM) technique used to calculate angle between two spectral vectors, a measure that is robust to variations in illumination and sensor response. In this study, 10-fold cross validation was adopted for model construction, meaning that 10 data partition schemes were used to model the same set of input-target data (Kucheryavskiy et al., 2020; Ludwig et al., 2018). The partial least squares (PLS) regression, and random forest regression (RF) algorithms were adopted to develop the model.

Results

The sensitivity of NO_3^- ions were observed at three spectral windows with range of the effective spectral window selected includes wavelengths: W1 (1460-1690 nm), W2 (1730-1780 nm), and W3 (1940-2150 nm). The comparison of different models reveals that RF machine learning techniques yield highly satisfactory results for predicting soil NO_3-N. RF regression resulted to be the best model in estimating soil NO_3-N under high and reduced soil sampling intensity compared to PLSR. Spectral matching techniques, spectral angle mapper (SAM) was adopted to reduce the soil sampling intensity of all study site years in a considerable manner.

Conclusion

This study demonstrated the potential of estimating surface soil NO_3-N with non-imaging hyperspectral data and reducing sampling intensity at the same time without compromising the accuracy of soil NO_3-N estimation. In contrast to the conventional method, where growers physically collect soil samples, send them to a lab for analysis, and then create a prescription, reflectance spectroscopy emerges as a promising non-destructive and expeditious alternative for producing prescription maps.

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