Synergistic use of PRISMA hyperspectral data and a random forest algorithm to map soil nutrients and chemical properties in sugarcane fields in Northeastern Thailand

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Abstract

Mapping and monitoring sugarcane crop health is essential for improving yield quality and supporting sustainable agriculture, particularly in Thailand, where sugarcane is an economically important crop. Soil fertility and nutrient availability strongly influence crop productivity; however, traditional soil sampling and laboratory analysis are time-consuming, costly, and limited in spatial coverage. Recent advances in Earth Observation (EO), especially hyperspectral remote sensing, provide new opportunities for large-scale soil monitoring. Hyperspectral data offers detailed spectral information across hundreds of narrow bands, enabling enhanced mapping and monitoring of soil properties (soil moisture, composition, and nutrient status). Hyperspectral data and powerful machine learning algorithms can provide accurate estimations of topsoil parameters across extensive crop field areas. This study mapped and monitored topsoil properties in 2025 in Northeast Thailand sugarcane fields using PRISMA hyperspectral imagery and a random forest (RF) algorithm. Six topsoil nutrients and chemical properties were analyzed, including electrical conductivity (EC), pH, soil organic matter (SOM), nitrogen (N), phosphorus (P), and potassium (K). Field data were collected from 37 sampling plots in March 2025, with 80% used for training and 20% for validation. PRISMA hyperspectral imagery was converted into analysis-ready data using cloud masking and reprojection. Results showed moderate to high performance (R^2 = 0.30–0.80), with high accuracy for N and SOM nutrient mapping. Spatial maps of the six topsoil nutrients and chemical properties exhibited smooth and consistent distributions for each sugarcane field, highlighting the distribution patterns of soil fertility and supporting sugarcane crop practices. The implemented study workflow was scalable and cost-effective for sustainable sugarcane management monitoring.

1. Introduction

The increasing number of Earth Observation (EO) satellites has revolutionized data access, especially PRISMA Hyperspectral data, fully funded by the Italian Space Agency (ASI). PRISMA combines a hyperspectral sensor with a medium-resolution panchromatic camera to provide rich spectral resolution. PRISMA hyperspectral sensors can determine the chemical and physical characteristics of an object's surface (Loizzo et al., 2018), offering several applications in the fields of environmental monitoring, resource management, crop classification, pollution control, and food security (Canero & Rodriguez-Galiano, 2026; Rossi et al., 2024).

Digital mapping and monitoring results of topsoil nutrients can be used to make decisions on crop cultivation and sustainable crop practices at the field level (Canero & Rodriguez-Galiano, 2026; Orynbassarova et al., 2025), while accurate soil nutrient maps serve as powerful tools for optimizing agricultural productivity and environmental sustainability (Mango et al., 2024). In Northeastern (NE) Thailand, over half of the land area is farmed, with rice, sugarcane, cassava and rubber the main economic crops (Som-ard et al., 2022; Suwanlee et al., 2023). Farmers in this region have adapted to a challenging environment by using long-standing climate-resilient practices to achieve sustainable agriculture.

However, the poor soil quality in NE Thailand, with low organic content and high salinity, leads to reduce crop yields (Arunrat et al., 2020; Thammasom et al., 2016). Government soil experts have supported the farmers, and accurate assessments of topsoil nutrients at the field level can help to optimize fertilizer application and crop management.

Satellite-based EO now offers rich information at near real time, providing high numbers of spectral bands (> 10 bands) (Canero & Rodriguez-Galiano, 2026). Many studies have shown the potential of using EO datasets together with powerful machine learning methods to accurately map topsoil at the field level over large regions (Cutting et al., 2024; Hosseinpour-Zarnaq et al., 2025; Zhang et al., 2023).

Many recent studies have shown the high potential of hyperspectral data in mapping and monitoring topsoil in crop fields. In 2019 and 2020, Rossi et al. (2024) mapped soil nutrients (Organic Matter (OM), Nitrogen (N), Phosphorus (P), and Potassium (K)) in Hebei Province, China using PRISMA hyperspectral data and machine learning regressions, resulting in Coefficient of Determination (R^2) values between 0.30 and 0.90. Canero and Rodriguez-Galiano (2026) estimated SOM and pH in the Sierra de las Nievesmountainous region of Southern Spain using PRISMA sensor data and several machine learning approaches, and obtained R^2 values of 0.36 and 0.42. while Hong et al. (2020) mapped topsoil OM at an agricultural

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field in the United States using airborne hyperspectral data and the RF algorithm, with results yielding R^2 at more than 0.75. AbdelRahman et al. (2025) integrated PRISMA data and several machine learning methods to map soil salinity and pH levels in Cairo, Egypt. They achieved R^2 results ranging from 0.30 to 0.90. Thus, many studies have demonstrated efficient soil mapping results and the potential of using hyperspectral data, together with machine learning algorithms to monitor soil nutrients in crop fields.

However, to the best of our knowledge, no comprehensive study has applied PRISMA hyperspectral data to simultaneously map soil nutrients and chemical properties (electrical conductivity (EC), pH, OM, N, P, and K) at the field level in Thailand.

To fill this research lacuna, this study applied PRISMA hyperspectral data and the RF regression algorithm with ground trough data to map the topsoil parameters EC, pH, OM, N, P, and K in sugarcane fields in NE Thailand. A topsoil nutrient index map was generated using four soil nutrient maps. The results can be used as a guideline for farmers to spread different types of fertilizers over sugarcane fields or other crops. Our proposed workflow can also be used to estimate soil nutrients over large areas under sugarcane and other crop cultivation.

2. Study Site and Data Used

2.1 Study Site

The study site was located at longitude 101°42.00' to 102°06.00' and latitude 16°18.00' to 16°42.00' in Khon Kaen Province, NE Thailand (Figure 1), with the main crops, including sugarcane, cassava and rice. The dominant economic sector in this region is agriculture due to the highly suitable geographical parameters.

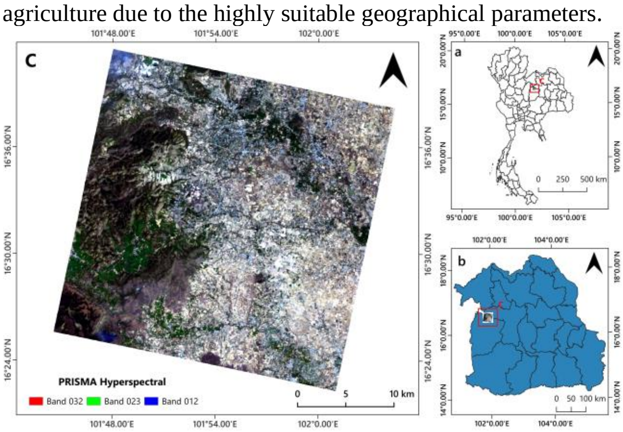

Figure 1. Study site in Khon Kaen Province, NE Thailand. The background shows the PRISMA hyperspectral data (RGB image composite), captured on 9 March 2025.

2.2 Free and Open-Source Software Used

In this work, we employed free and open-source software, including QField application, QGIS version 3.44.7 and R version 4.2.2, for mapping and monitoring across NE Thailand. Details of the software and tools used in this study are summarized in Table 1.

Software	Plugins/Package	Description
QField	- QField Sync	- used a tool to collect the soil samples
QGIS version 3.44.7	- Point Sampling Tool - Layout manager	- extracted the spectral information to field plots - used to design the maps
R version 4.2.2	- "*prismaread*" - "*random forest*"	- used to preprocessing PRISMA dataset - used to train and predict the soil nutrients.

Table 1. The details of software, package and description used for this study.

2.3 Reference Data

This study analyzed 37 samples (plot: 5 x 5 m) of topsoil to map EC, pH, OM, N, P, and K in sugarcane fields. Six topsoil samples were collected randomly within each sugarcane field between 15 and 19 March 2025 during the bare-soil period when the topsoil was exposed. The geographic coordinates of each sampling location were recorded using a QField application. Before sampling, all the vegetation, stones, and other surface materials were removed. The topsoil samples were collected at 15-20 cm depth, stored in plastic bags, and transported to the laboratory for analysis.

The soil samples were naturally air-dried, followed by sieving to eliminate impurities. Soil pH and EC were measured using the potentiometric method. Soil OM content was determined by the potassium dichromate oxidation method with external heating. Total N was examined using the Kjeldahl method, with available P and exchangeable K determined by the antimony colorimetric method and flame photometry, respectively. All the laboratory analyses were conducted by Mitr Phol Sugarcane Research and Development Center Co., Ltd.

2.4 PRISMA Hyperspectral Data

PRISMA hyperspectral imagery Level 2D (L2D) data were collected from the PRISMA user portal (https://prismauserregistration.asi.it/). The PRISMA imagery was acquired on 9 March 2025, close to the fieldwork period. This dataset consisted of 230 spectral bands spanning the visible, near-infrared (VNIR), and shortwave infrared (SWIR) regions (400–2500 nm) at a spatial resolution of 30 m. All the image bands were preprocessed (cloud masking) and converted into analysis-ready data using the prismaread package within the R environment. This package enables the extraction, management, and preparation of PRISMA hyperspectral products (Busetto & Ranghetti, 2020). All the spectral bands were used for this analysis.

Vegetation indices (VIs) can improve predictive model performance. This study selected Normalized Difference Vegetation Index (NDVI) (Rouse et al., 1974), Soil-Adjusted Vegetation Index (SAVI) (Huete, 1988), Normalised Difference Water Index (NDWI) (Serrano et al., 2000), Green Normalized Difference Vegetation Index (GNDVI) (Gitelson et al., 1996), Enhanced Vegetation Index (EVI) (Huete et al., 2002), and Ratio Vegetation Index (RVI) (Kaufman & Tanre, 1992).

2.5 Geographical Dataset

Climate and elevation data were used to improve the RF predictive models. Mean temperature and rainfall data were collected from WorldClim Version 2 at a spatial resolution of 1

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km² (Fick & Hijmans, 2017). Elevation data were obtained from the Shuttle Radar Topography Mission, which offers 30 m resolution data from radar interferometry (Farr et al., 2007). These raster datasets were preprocessed to match the 30 m pixel sizes of the PRISMA hyperspectral imagery.

3. Soil Nutrient Mapping

The workflow followed three main steps as data collection, soil nutrient model development, and results evaluation (Figure 2). The dataset was divided into 30 sampling plots (80%) for the training set and 7 sampling plots (20%) for independent validation using R software version 4.2.2.

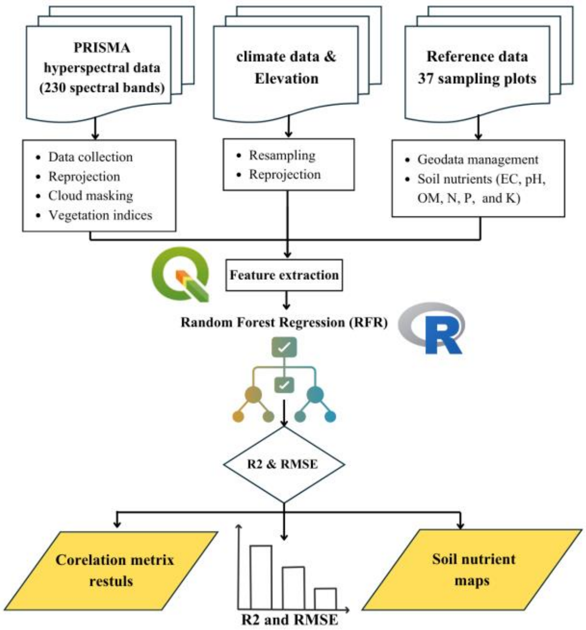

Figure 2. Implemented workflow for mapping soil nutrients using PRISMA hyperspectral data and a random forest (RF) algorithm.

3.1 Feature Measurement

The RF algorithm was applied to improve model performance and reduce computational complexity. RF was also used to identify the most important features for soil nutrient estimation (Breiman, 2001). In the analysis, all 230 PRISMA hyperspectral bands and an additional six VIs were evaluated, with the most relevant variables selected as input features for soil nutrient mapping. The top features of PRISMA hyperspectral data were synthesized using SHapley Additive exPlanations (SHAP) to explain the variable results from the RF model (Lundberg & Lee, 2017).

3.2 Soil Nutrient Model

A Random Forest Regression (RFR) algorithm was used to estimate soil nutrient mapping. The RFR is a widely used machine learning algorithm in remote sensing applications due to its robustness and strong predictive performance (Breiman, 2001). The RFR normally requires two hyperparameters as the number of tree (ntrees) and the number of features sampled at each split note (mtry).

In this study, 30 training plots and the selected important features (spectral information and VIs) were used to estimate soil nutrients in sugarcane fields. The RFR predictive model was tuned by testing ntree values ranging from 500 to 1000 (increment = 10), while retaining the default mtry setting. The best hyperparameter was achieved with 500 trees and this was used to map the six-soil nutrient and chemical properties as EC, pH, OM, N, P, and K at the field level. The resulting maps were classified into five categories as very low, low, moderate, high, and very high, and normalized and integrated to generate a composite soil nutrient and chemical property index map.

3.3 Accuracy Assessment

The soil nutrient and chemical property map results were evaluated for accuracy by the Root Mean Square Error (RMSE) and Coefficient of Determination (R^2) using an independent validation dataset (7 sampling plots: 20%).

4. Results and Discussion

4.1 Important Feature Selection

The ten most important features are summarised in Figure 3, showing the variable importance rankings of the six-topsoil nutrient and chemical properties, including EC, OM, pH, N, P and K. The importance scores showed the relative contribution of the hyperspectral bands and geographical datasets for each predictive model. The most important features of the EC predictive model were the SWIR spaces, particularly bands between 1425 and 1625 nm, leading to the strong sensitivity of the soil properties. Similarly, OM was primarily influenced by the SWIR bands, highlighting their sensitivity to OM absorption features and soil composition. Rossi et al. (2024) also reported that the SWIR bands were strongly related to P and K nutrients. The pH demonstrated several bands, including the visible and near-infrared spaces that contributed to improving the RF predictive model and indicated their relationship with soil mineralogical and chemical properties. In N soil, elevation was the most important feature, highlighting the effects of landscape and spectral information on nitrogen distribution over different crop fields.

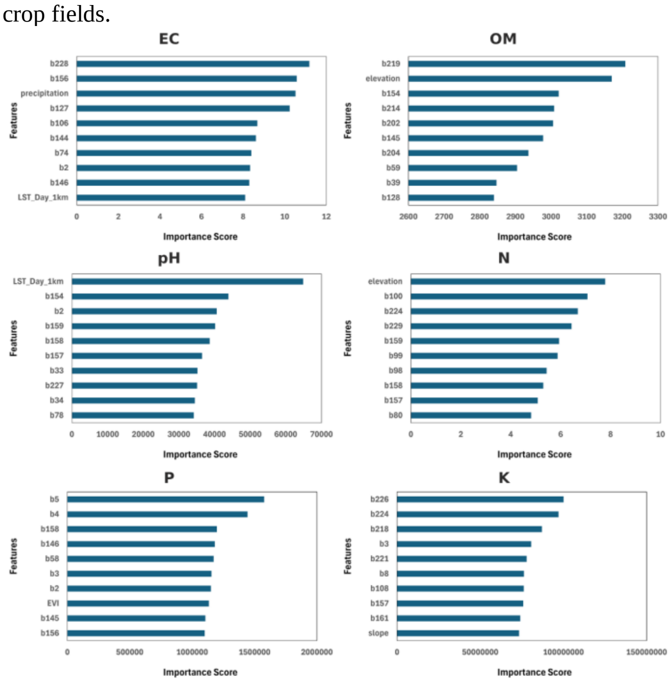

Figure 3. The top ten important features for monitoring topsoil nutrients and chemical properties using a random forest (RF) algorithm and training dataset. The b1-b230 are spectral bands of PRISMA hyperspectral data.

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The SHAP plots showed the influence of the most important features on the RF models developed for estimating each topsoil sample (Figure 4). Each point represents an individual sample, with color indicating the magnitude of the predictor value (blue = low, pink = high). PRISMA hyperspectral bands, particularly within the SWIR, NIR, and red-edge spaces, were the dominant features across the 230 models. The elevation contributed significantly to N prediction. The results highlighted the effectiveness of hyperspectral remote sensing for explaining topsoil properties. The horizontal axis demonstrated the SHAP values, highlighting the positive or negative contribution of each variable to the model result.

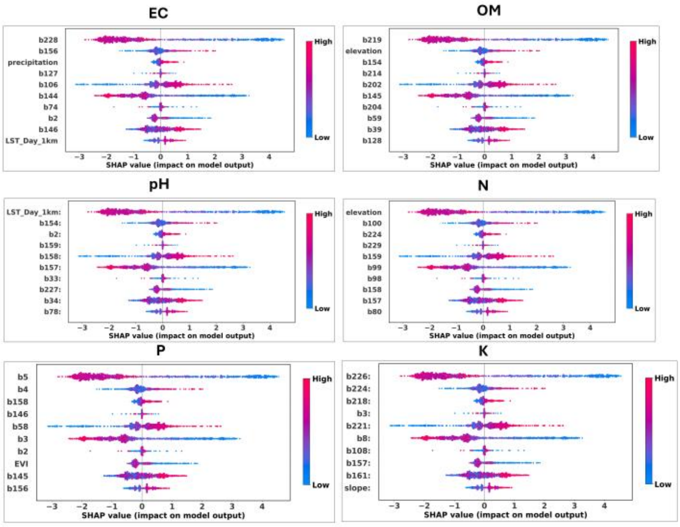

Figure 4. The SHapley Additive exPlanations (SHAP) values of the top ten important feature results from random forest (RF). The b1-b230 are spectral bands of PRISMA hyperspectral data.

4.2 Estimating Soil Nutrients and Chemical Properties

Figure 5 shows scatter plots of the relationships between the estimated soil nutrients and chemical properties mapping results derived from the six RFR predictive models as EC (a), OM (b), pH (c), N (d), P (e), and K (f). The blue solid line represents a 1:1 relationship, while the red dashed line displays the fitted linear relationship. The mapped results had R^2 values between 0.32 and 0.77.

High R^2 values were observed for OM, K, and N indicating the potential and reliability of the topsoil mapping results. However, the P map showed a weak relationship due to the reduced range of training data values, leading to poor performance of the RFR predictive model. This result concurred with Rossi et al. (2024) and AbdelRahman et al. (2025), who demonstrated high efficiency of topsoil mapping using PRISMA hyperspectral data. Our study confirmed that the RFR predictive model effectively estimated topsoil parameters at the sugarcane field level.

Spatial distribution maps of the six topsoil nutrients and chemical properties were generated at the field scale within the sugarcane cultivation areas. The results showed considerable spatial variability in soil property levels (Figure 6). Colored polygons represent the estimated nutrient status of individual sugarcane fields.

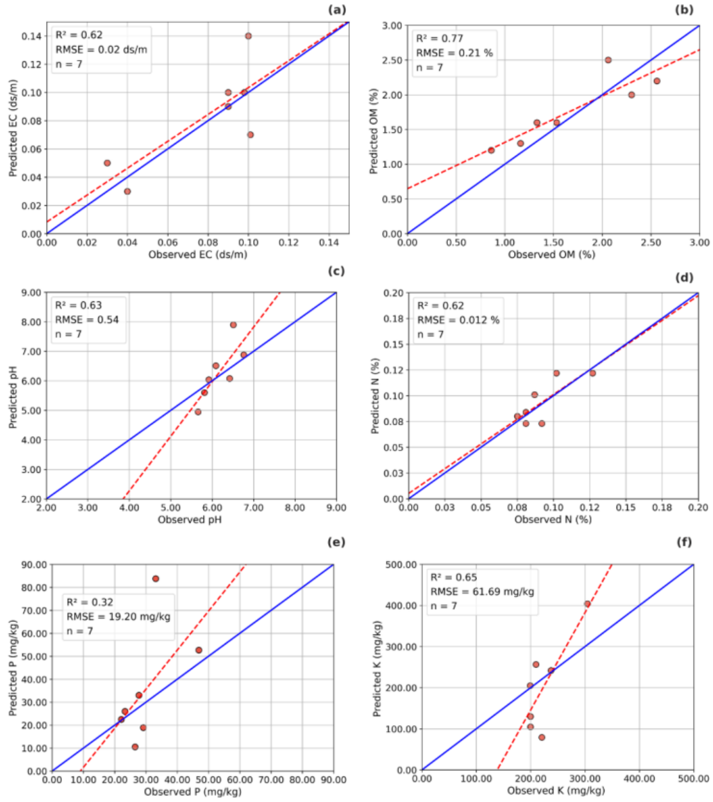

Figure 5. Scatter plots showing the performance of six random forest (RF) predictive models for estimating soil nutrients and chemical properties, including electrical conductivity (EC), organic matter (OM), pH, nitrogen (N), phosphorus (P), and potassium (K).

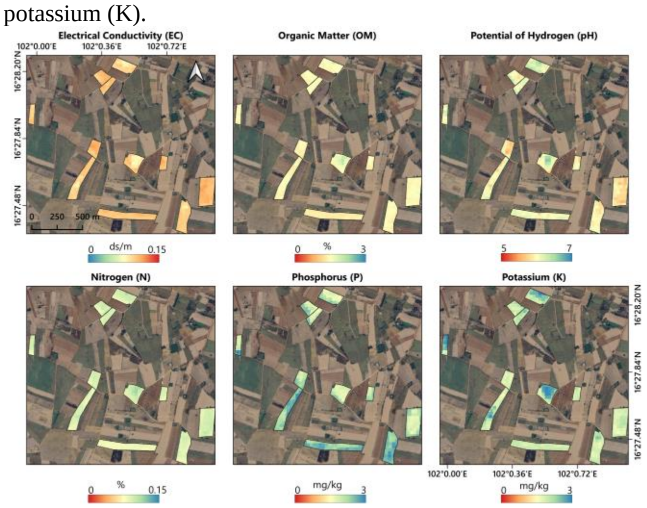

Figure 6. Spatial distribution map result of soil nutrients and chemical properties including electrical conductivity (EC), organic matter (OM), pH, nitrogen (N), phosphorus (P), and potassium (K) at sugarcane field levels.

The results displayed spatial variability in soil nutrients and chemical properties across the study area (Figure 6). The 30 x 30-meter pixel values reflected differences in soil characteristics, crop management practices, fertilization history, and environmental conditions at the field level (Canero & Rodriguez-Galiano, 2026). The mapped results provided detailed field-scale information on soil fertility status and nutrient availability, enabling the identification of nutrient-deficient zones. These mapped results showed the potential of

PRISMA hyperspectral data and the optimized RFR model for mapping crop nutrients at the field level to promote sustainable crop management (Cutting et al., 2024; Hong et al., 2020; Hosseinpour-Zarnaq et al., 2025). Our findings can be used to better understand sustainable crop practices.

Figure 7 demonstrates that the spatial distribution of the six topsoil nutrients and chemical properties across sugarcane fields as EC, OM, pH, N, P, and K varied substantially. Many sugarcane fields displayed high nutrient concentrations. The mapped results were divided into five groups as very low (1), low (2), moderate (3), high (4), and very high (5). The spatial distribution patterns indicated that soil fertility was not uniformly distributed across the crop fields (Arunrat et al., 2020). Our findings highlighted the efficiency in mapping topsoil nutrients at the field-scale to enhance fertilizer application for sustainable sugarcane cultivation.

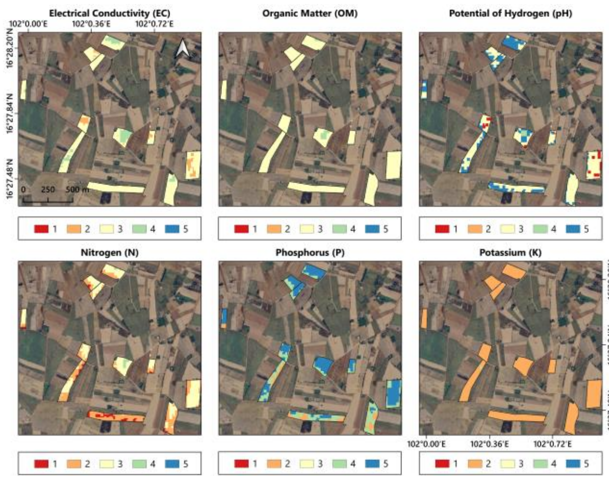

Figure 7. Spatial distribution of soil nutrients (30 x 30 m) in sugarcane fields, classified into five groups as (1) very low, (2) low, (3) moderate, (4) high, and (5) very high.

The nutrient index map showed distinct fertility zones across the five nutrient levels (Figure 8). The spatial correspondence between the spectral information and the nutrient classes allowed the hyperspectral imagery to effectively observe the differences in soil properties, enabling a detailed field-scale assessment of soil fertility.

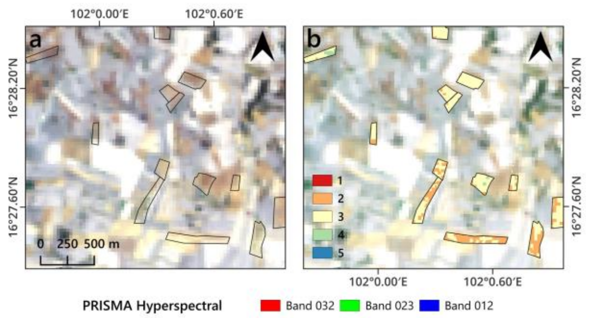

Figure 8. Comparison between PRISMA hyperspectral imagery (RGB composite) and the derived soil nutrient index map.

4.3 Study Uncertainty and Limitations

This study demonstrated the potential of mapping soil nutrients and chemical properties in sugarcane fields using the best RFR predictive model and PRISMA hyperspectral data, but some limitations must be recognized, as listed below.

- The limited number of samplings led to model generalization errors and uncertainty in map accuracy. Future studies should increase the number of reference samples to improve predictive model robustness and mapping performance.
- This study achieved high accuracy results for mapping topsoil nutrients and chemical properties before the crop growing season. However, comprehensive digital soil maps generated after harvest for the same fields are required to better support field-level crop management and decision-making throughout the production cycle.
- Evaluating AlphaEarth Foundation (AEF) datasets for soil nutrients and chemical properties mapping offers high potential.
- Only PRISMA hyperspectral sensor data were used in this study, and integrating multi-temporal EO datasets may improve the stability and accuracy of the estimation results.
- This study mapped soil nutrients for sugarcane fields under bare-soil areas. Future research should investigate bare-soil identification and soil reflectance characteristics using EO data and advanced machine learning or deep learning methods to improve the reliability and consistency of the results.

5. Conclusions

This study mapped six topsoil nutrients and chemical properties as electrical conductivity (EC), organic matter (OM), pH, nitrogen (N), phosphorus (P), and potassium (K) in sugarcane fields in NE Thailand in 2025 using PRISMA hyperspectral data and RFR. The results produced consistent field-level nutrient maps. The proposed workflow can be readily adapted and applied to soil nutrient mapping in other crop production systems. However, the analysis was based on a single-date PRISMA hyperspectral imagery, the RFR method, and a limited number of reference samples. Future studies should incorporate multi-temporal EO datasets and larger reference datasets to improve the model robustness and accuracy. Monitoring the temporal changes in soil nutrient conditions should also be considered to improve crop yields in each field.

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