Spectral Discrimination of Crop Types Based on Hyperspectral Sensor

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Abstract: Agriculture is the art of producing different crop types from the soil and plays an important role in our lives, sustaining and improving the economic sector. This study is mainly focused on discrimination of crop types based on space-borne hyperspectral (PRISMA) sensor over Khanna, Amloh, Bassi Pathanan blocks within Punjab state, India. Hyperspectral sensor consists of narrow bands and provide precise, continuous spectral signature which can significantly help to obtain an unambiguous distinction among the crop types. A total of 135 individual points were surveyed during paddy growing season (May and June month) and the main crop types over study area were maize, sunflower, moong, sugarcane, chilli. The collected end-member spectra of same crop types at different sites were averaged to produce reference spectra for various specimens. Each collected field data was accompanied with photo record. The results of the study will help to improve the accuracy of crop mapping and crop condition assessment.

Keywords: Sustainable Agriculture, Paddy Crop, Spectral Signature, Spectral Vegetation Indices

1. Introduction

Agriculture is a vital global sector, contributing 6% of the world's economy and providing employment to nearly half of India's population. Accurate crop information supports food security, water management, and poverty reduction. Remote sensing, particularly hyperspectral imaging, has become crucial for crop type discrimination due to its efficiency over traditional, labor-intensive methods. Hyperspectral sensors provide detailed spectral data, essential for distinguishing crop types based on unique plant characteristics. This study leverages PRISMA hyperspectral imagery to map crop types in Punjab, India, aiming to improve crop mapping and assessment accuracy. These advancements could support sustainable agriculture by providing critical insights into crop health and yield predictions.

2. Study Area

Punjab, located in northwest India, is an agrarian state reliant on river water for irrigation, with key crops including wheat, rice, and cotton. The study focuses on diverse crop patterns within Ludhiana, Fatehgarh Sahib, and Patiala districts, covering ~890 km^2 and including blocks like Khanna and Amloh, with crops such as maize, sunflower, and sugarcane

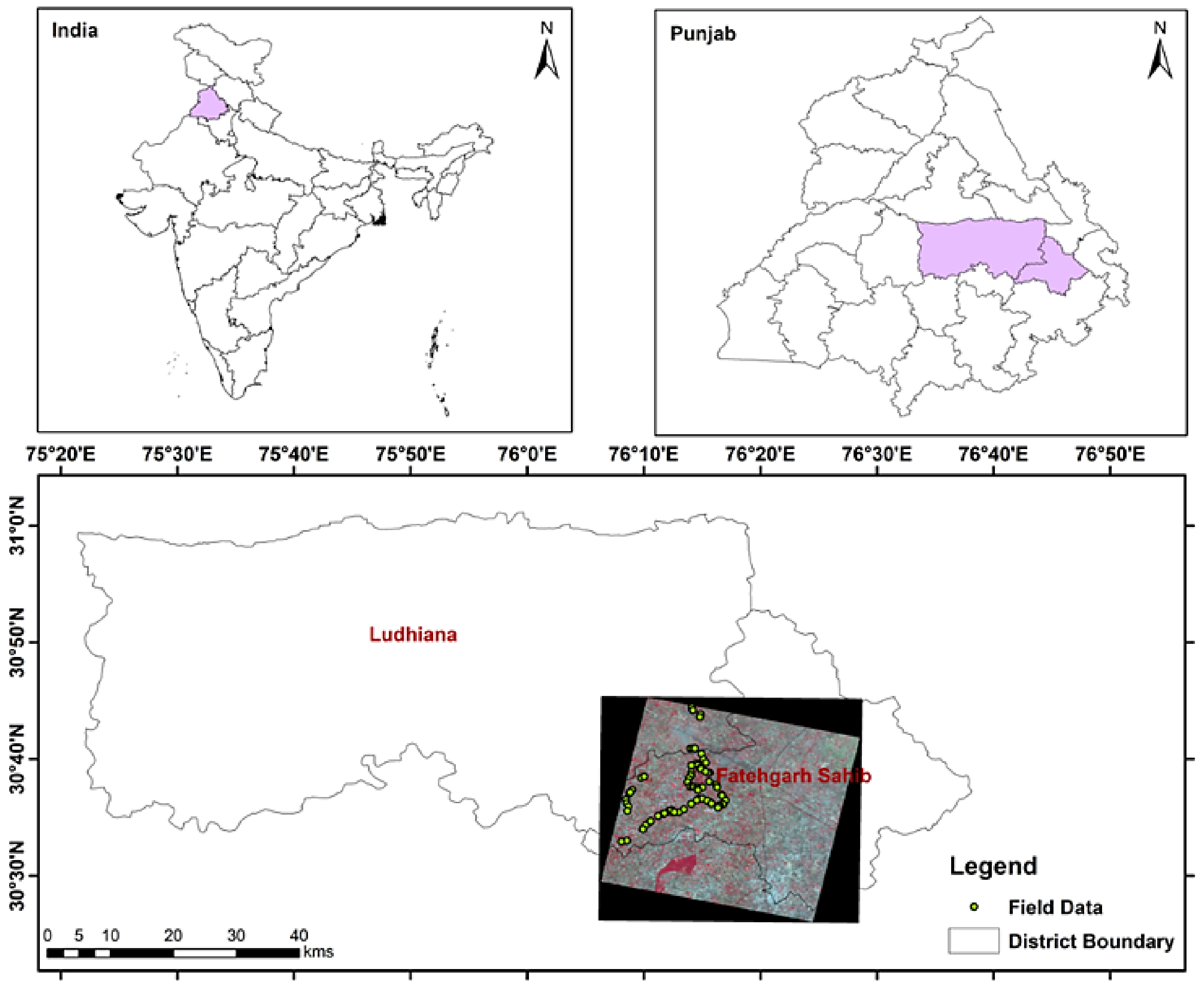


Figure 1: The location of field data collection over study area overlaying a False Color Composite (FCC) PRISMA hyperspectral image captured on 06 June 2022.

3. Materials and Methodology

The research methodology in this study involves four stages: literature review, data acquisition, data processing, and analysis. PRISMA hyperspectral data, taken concurrently with field sampling, facilitated effective crop identification. Field data were collected in May–June 2022 during the paddy season using GPS, covering 135 points for key crops like maize and sunflower. Analysis utilized software such as ENVI, ArcMap, QGIS, and Matlab.

3.1. Field Data Collection:

Field data collection, conducted during the paddy season (May and June), was crucial for identifying crop types and developing a spectral library. Using a GPS with ±3 m accuracy, 135 individual points were surveyed across the main crop types (maize, sunflower, moong, sugarcane, and chili), each documented with photo records.

3.1. Field Data Collection:

(a) Maize (b) Sunflower (c) Sugarcane

(d) Moong (e) Chili (f) Fallow land

Figure 2: Ground truth data for (a) maize; (b) sunflower; (c) moong; (d) sugarcane; (e) chili; and (f) fallow land observed across the study area during the field visit.

4. Results and Discussion:

The study utilized PRISMA hyperspectral imagery from June 2022 to develop a spectral library for crop types in Punjab, India, specifically in Khanna, Amloh, and Bassi Pathanan. The hyperspectral data, collected across 234 spectral bands, allowed for accurate discrimination and mapping of crop types based on visible and near-infrared bands. Field data were collected simultaneously, covering five crops (maize, moong, sugarcane, sunflower, and chilli) and six other features. By averaging spectral data from multiple sites, the study produced reference spectra, aiding in crop mapping. The analysis highlighted key spectral bands for maize and rice identification, showcasing the effectiveness of narrowband indices for crop pigment analysis.

Hyperspectral sensors capture crop reflectance across multiple wavelengths, particularly sensitive to chlorophyll and canopy structure. While all five crops showed similar reflectance trends, chili had the highest reflectance across the spectrum. Maximum reflectance occurred in the infrared (940-1300 nm), with lower reflectance in 1361-1449 nm and 1822-1932 nm, and the lowest in 2350-2495 nm. The visible region (400-650 nm) had low reflectance due to chlorophyll absorption, while the red-edge (~700 nm) and near-infrared (750-900 nm) provided useful differentiation for crop types. The NIR zone proved best for crop type discrimination, aiding image classification and crop health analysis.

Table 1: Sensitive wavelengths (peaks and troughs) of each crop from the spectral signature.

Crop	Sensitive wavelength region (nm)	
	Peak	Trough
Maize	700-1284, 1459-1811, 1961-2070	1373-1459, 1822-1932,
Sunflower	1196-1284, 1470-1824	1373-1450, 1820-1950
Sugarcane	988-1110, 1240-1328, 1510-1750,	1371-1415, 1823-1932
Moong	712-909, 1196-1320, 1502-1784,	1373-1416, 1822-1932
Chili	988-1110,1152-1320,1586-1784	1373-1420, 1822-1932
Fallow Land	943-962,1196-1320,1502-1784	1373-1416, 1830-1930
Cultivated Land	1196-1328, 1520-1780	1373-1416, 1830-1930
Water	1029-1152, 1240-1284	1375-1390, 1822-1930
Algal Bloom	943-962, 1029-1152, 1196-1284	1375-1416, 1830-1932
Built-up	1240-1284, 1502-1784	1375-1416, 1830-1932
Tree Cover	943-962, 1240-1284,	1375-1416, 1830-1932

5.Conclusion:

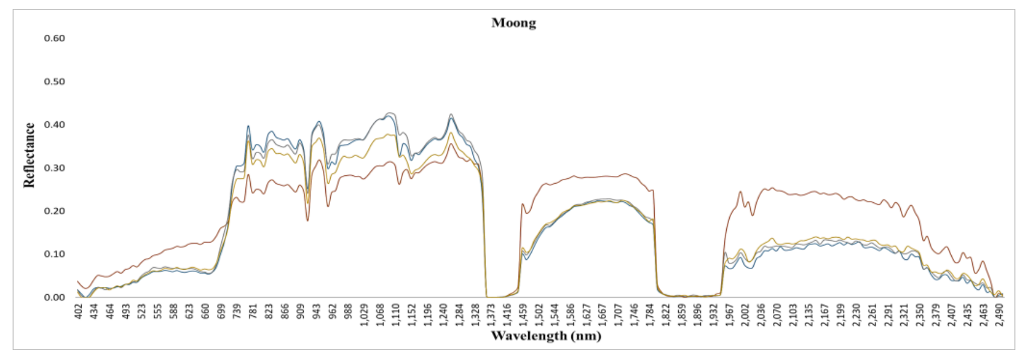
This study concludes that hyperspectral remote sensing, along with high spatial and spectral resolution, is an effective tool for discrimination and classification of crop types. Crop types were effectively distinguished on the basis of their spectral signatures. The red and infrared portions of the electromagnetic spectrum are the most employed and potential wavelength regions for chlorophyll estimation and provide vegetation growth. This study also revealed that the spectral reflectance patterns of all the crop types were similar and that it was very difficult to discriminate them. Spectral signatures of different features can improve supervised categorization accuracy via machine learning. Compared with broad bands, the narrow bands of hyperspectral data offer significantly more information in terms of quantifying the biophysical properties of agricultural crops. The spectral signatures of various features and classification results can be further used for yield prediction for crops, which can increase food security.

Author Contributions: Kusum Lata: data collection, original draft preparation, software; Mohit Arora: conceptualization, methodology, software, internal review; Navneet Kaur: overall guidance and internal review.

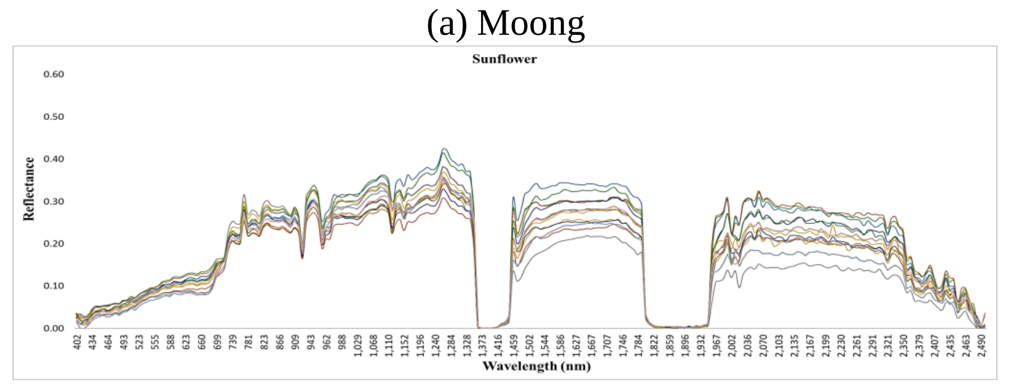
Data Availability Statement: The data that support the findings of this study are available from the corresponding author upon reasonable request.

datasets. We also express our gratitude to the anonymous reviewers for their insightful criticism.

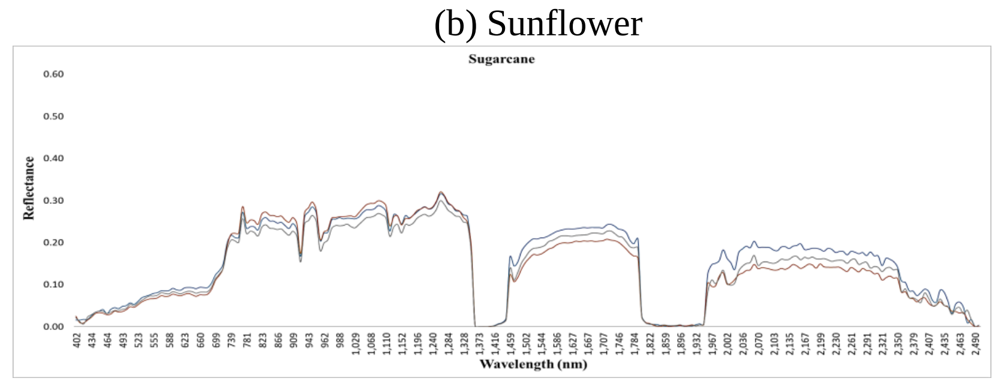
Conflicts of Interest: The authors declare no conflicts of interest.



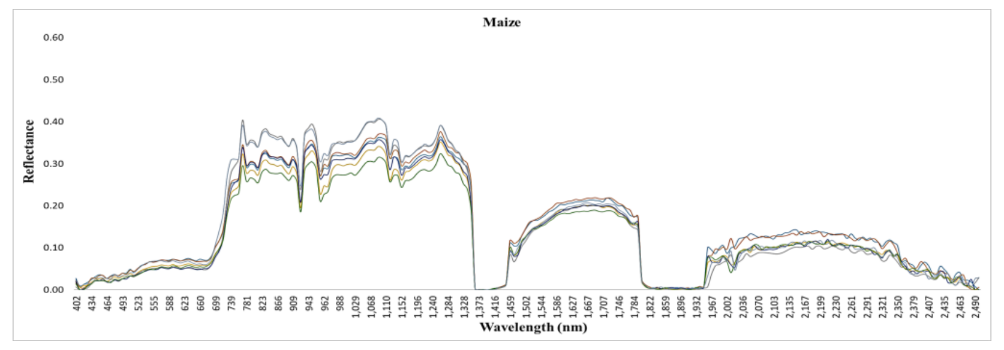
(a) Moong



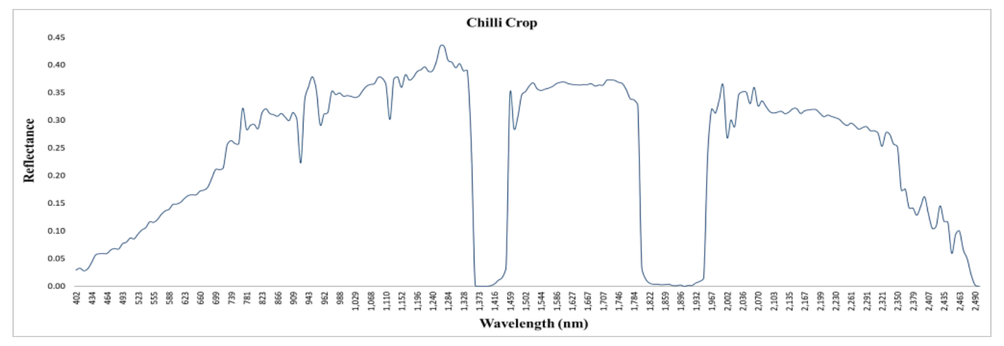
(b) Sunflower



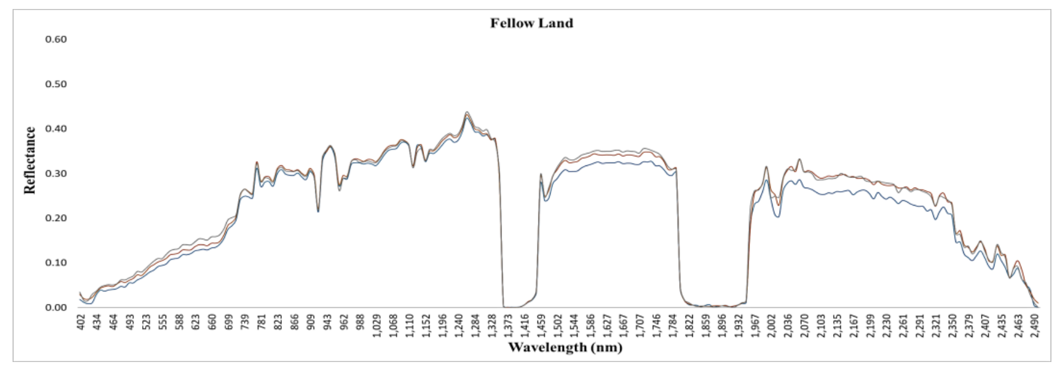
(c) Sugarcane



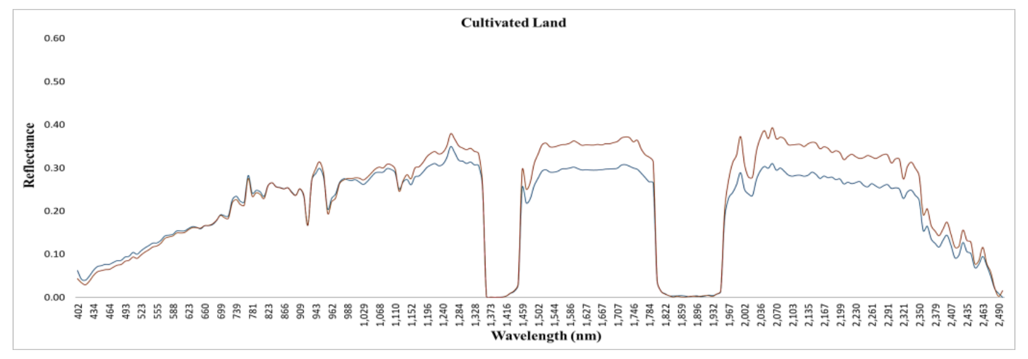
(c) Maize



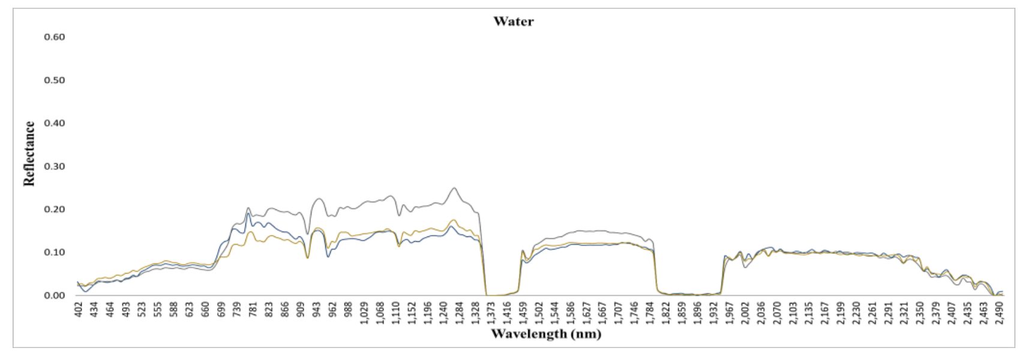
(d) Chilli



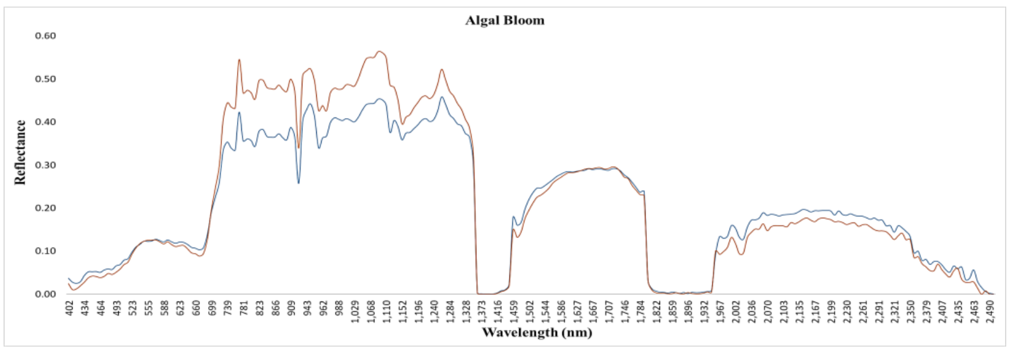
(e) Fallow Land



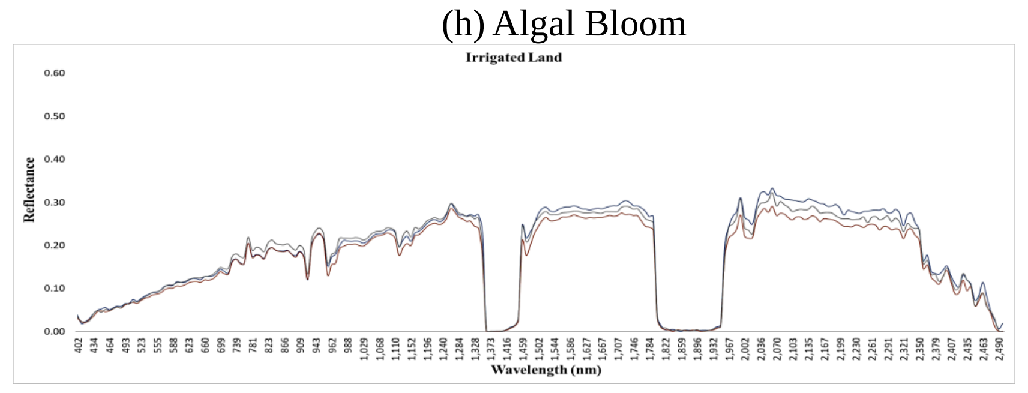
(f) Cultivated Land



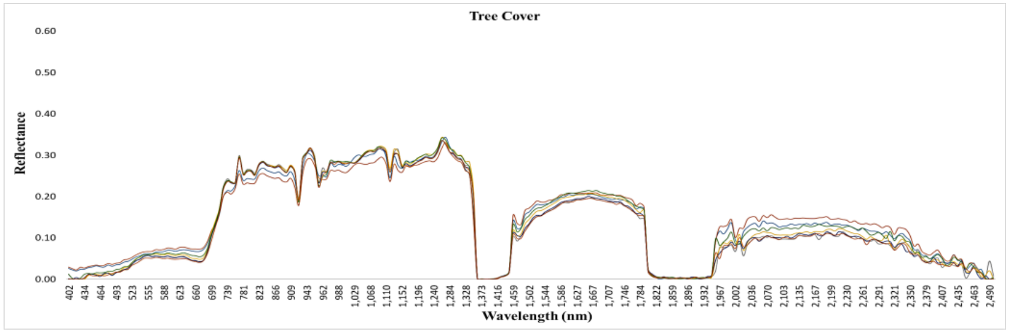
(g) Water



(h) Algal Bloom



(i) Irrigated Land



(j) Tree Cover

Figure 3: Spectral signatures of different crop types (a) Moong (b) Sunflower (c) Sugarcane (d) Maize (e) Chilli (f) Fellow Land (g) Cultivated Land (h) Water (i) Algal Bloom (j) Built Up (k) Irrigated Land (l) Tree Cover

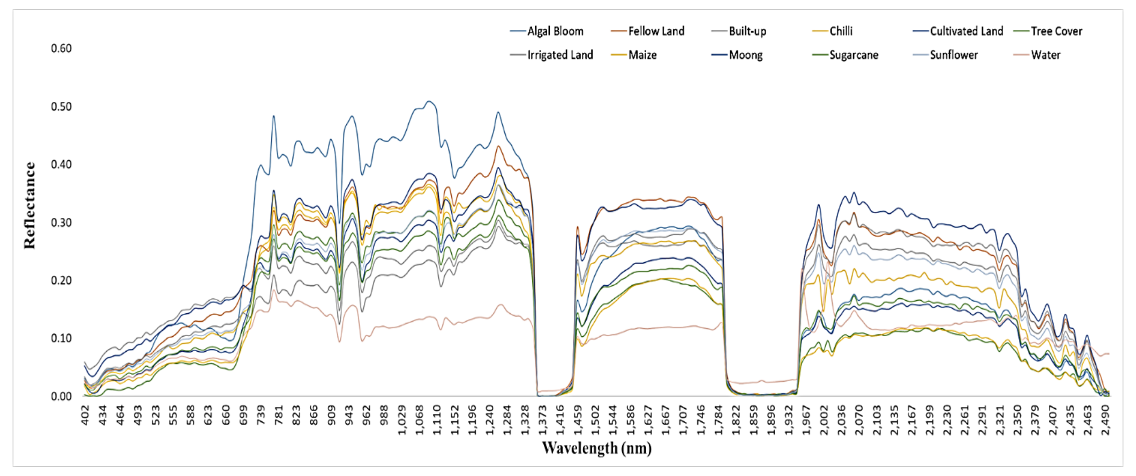


Figure 4: Average reflectance spectra of crop types and other features at different sites across the study area.

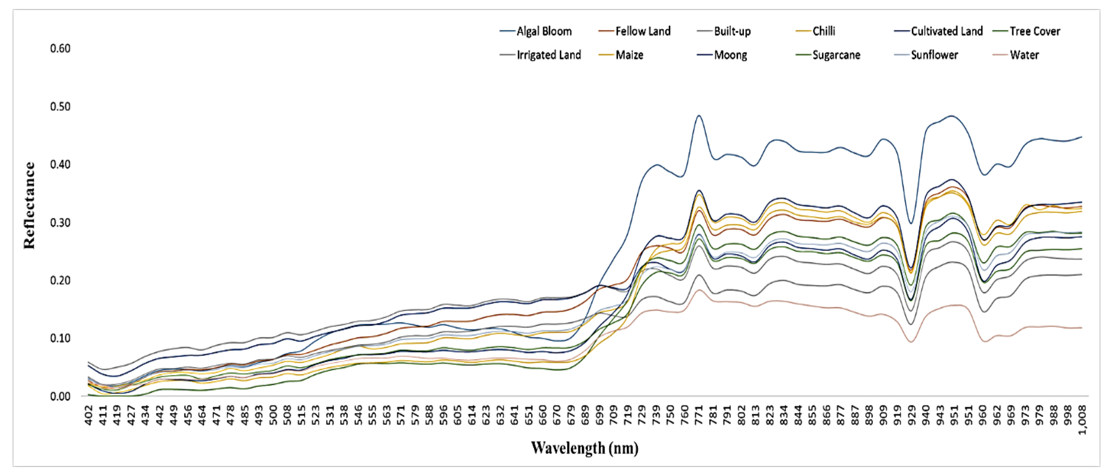


Figure 5: Average reflectance spectra of crop types and other features in the spectral range of 400–1000 nm across the study area.

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