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Proceeding Paper

Spectral Discrimination of Crop Types Based on Hyperspectral Sensor †

Kusum Lata [1,*], Mohit Arora [2] and Navneet Kaur [1]

[1] Department of Computer Science Engineering, Chandigarh University, Mohali 140307, Punjab, India; navneetsehgal5@gmail.com
[2] Punjab Remote Sensing Centre, Ludhiana 141004, Punjab, India; mohitarora.prsc@gmail.com
* Correspondence: kusum.e17456@cumail.in

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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 which lies in 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

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1. Introduction

Agriculture plays an important role in our lives, sustaining and improving the economic sector and also helps in ensuring food security across the globe. The field of agriculture adds up to 6% of the world's economy and it is a dominant sector in at least nine countries of the world. Agriculture is one of the most important and sensitive sector of the Indian economy that provides employment to almost half the populations of the country. It is essential to obtain real information about the type, health, location, extent, and yield of crops for assurance of food security, water resource management and poverty reduction (Seydi et al., 2022).

Remote sensing based crop types discrimination has gained importance for agricultural research. In situ crop type discrimination is frequently expensive, labor-intensive and destructive. A large number of remote sensing sensors including multi-spectral optical sensors, microwave synthetic aperture radar, light detection and ranging (LiDAR), hyperspectral sensors and techniques have been employed for periodic assessment and monitoring of crops at different sites (Veloso et al., 2017; Xie et al., 2019a,b). Such sensors dimensions control the type and to extract detailed information from an image. Remote sensing data contain rich spectral features that characterize crop leaf pigment, leaf water content and canopy structure, and spatial features that reflect crop planting morphology and texture, particularly when high spatial resolution images are considered (Chen et al., 2022). Multispectral sensors have limited their ability to resolve agricultural crop types and can differentiate three to six classes of crop types with overall accuracy of 60–75%. The improvements in remote sensing sensors in the studies of crop types have been significantly boosted with the launch of hyperspectral sensors with enhanced spatial and spectral resolution. Spectral resolution is more important than spatial resolution for providing accurate figure of species discrimination and classification of crops. There are many difficulties linked with extracting valuable information with confidence from spatial resolution imagery. Hyperspectral imaging techniques are now in use for over two decades and come as a reasonable and rapid mode for taking measurements of spectral reflectance. Very limited research has been done on crop discrimination based on hyperspectral remote sensing sensors (Meng et al., 2021; Marshall et al., 2022). Precise and continuous spectral signature can significantly help to obtain an unambiguous distinction among the crop types (Liu et al., 2022). The spectral signatures reflected from the plant canopy at specific wavelengths provide various types of cumulative information on the substantial and gradual changes that occur in specific plant characteristics or tolerance levels (El-Hendawy et al., 2019). Hyperspectral sensors with narrow spectral bands may be crucial for providing information of crop biophysical characteristics and yield prediction.

The study is mainly focused on PRISMA hyperspectral imagery data for discrimination of crop types. Hyperspectral data have been taken over Khanna, Amloh, Bassi Pathanan blocks which lies in part of Punjab state, India. Hyperspectral imagery data is mainly used for development of spectral library of diverse crop types including maize, sunflower, moong sugarcane, chilli. The results of the study will be helpful for the evaluation of the hyperspectral data for agricultural prospects. It may help to improve the accuracy of crop mapping and crop condition assessment. Sustainable agriculture is not a set of prescriptive management practices and is defined differently by different people to accommodate individual scientific, political, or economic agendas.

2. Study Area

Punjab state is located in the northwest region of India. Punjab is predominantly an agrarian state which is highly dependent on river water for irrigation and domestic purposes in non-monsoon period and the main economic activity in the area is with chief crops being wheat, rice, cotton, etc. The study area was selected for crop types study because of consisting varying crop pattern and carried over a part of Ludhiana, Fatehgarh Sahib and Patiala district of Punjab state, India and area lies between 30°26′ N to 30°45′ N latitude and 76°06′ E to 76°28′ E longitude with a total area of ~890 km² (Figure 1). The block lies in the study area are Khanna, Amloh, Bassi, Pathanan over Punjab state, India and its primarily grown crops during study period are maize, sunflower, moong sugarcane, chilli, rice, etc.

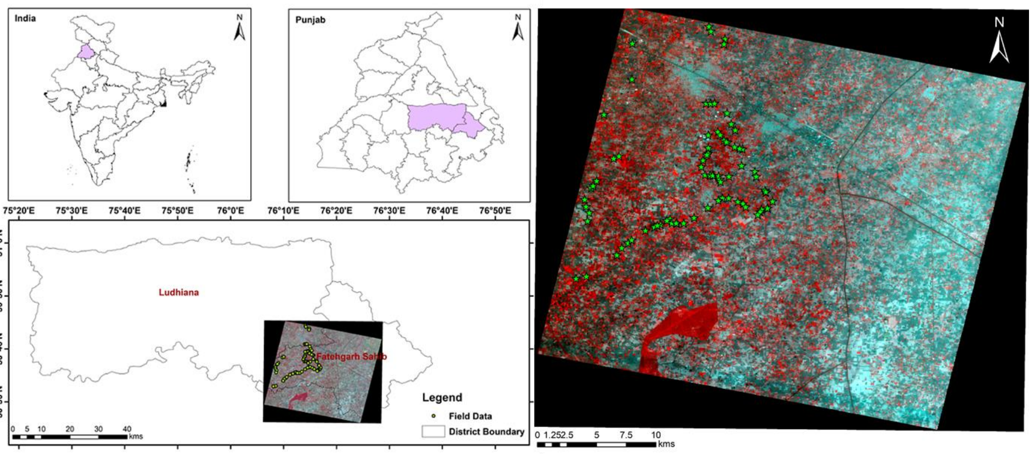


Figure 1. The location of field data collection over study area overlaying a False Color Composite (FCC) PRISMA hyperspectral image captured on 06 June 2022.

3. Materials and Methodology

The research methodology used in this study has been divided into four main stages includes literature review, data acquisition, data processing, data analysis and representation. This study used field sampling points and one hyperspectral remote sensing atmospherically corrected datasets (i.e., PRISMA) over the study area for the effective identification of crop types. Different image processing techniques have been developed for the corrections of satellite image. Hyperspectral data has been taken on the same time during the field survey data. The field data collections period was between May and June 2022 and acquisition period for selected images were between 05 to 06 June 2022. The selected image was cloud free or uncovered. The analysis was performed using ENVI 4.7, ArcMap 10.8, QGIS and Matlab 2018a software.

3.1. Field Data Collection

Field data collection is essential to identify the crop types present in a study area. Extensive field work was carried out during paddy season (May and June month) to acquire the locations of crop types for creation of spectral library and classification. The geographical coordinates of each crop were measured using a handheld GPS with a position accuracy of +3 m. A total of 135′ individual points were surveyed and the main agricultural crop types over study area were maize, sunflower, moong sugarcane, chilli. Each collected field data was accompanied with photo record (Figure 2).

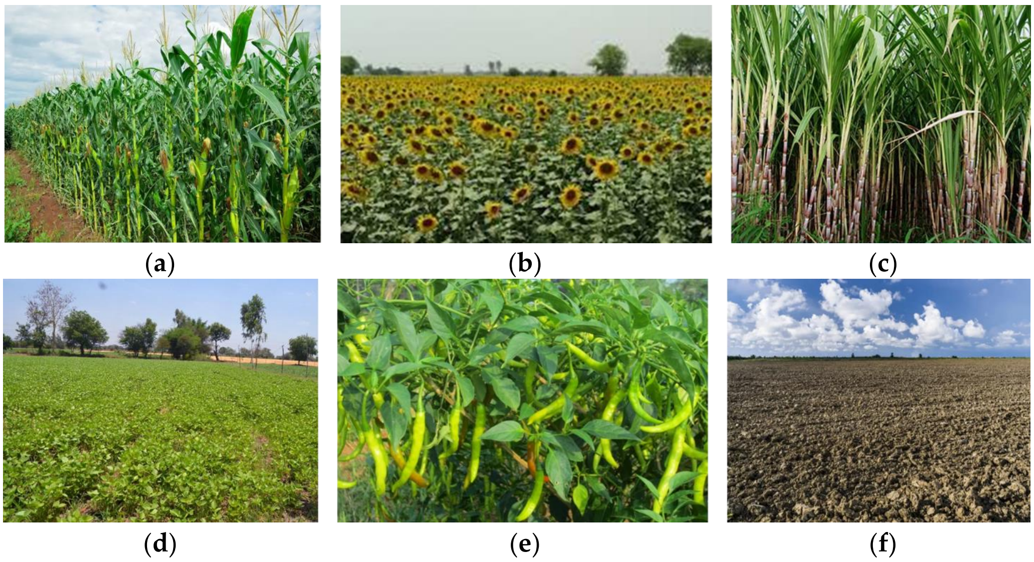


Figure 2. Ground truth data for (**a**) maize; (**b**) sunflower; (**c**) moong; (**d**) sugarcane; (**e**) chili; and (**f**) fallow land observed across the study area during the field visit.

3.2. PRISMA Hyperspectral Data

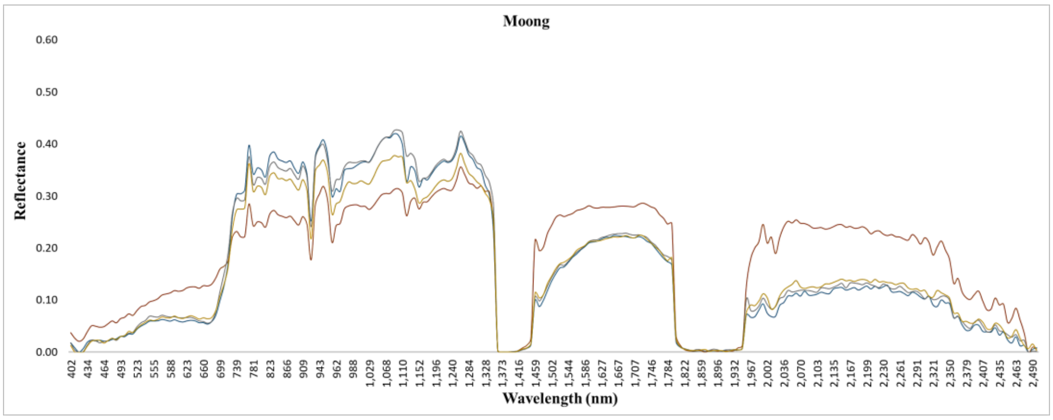
The Italian Space Agency (ISA) PRecursoreIper Spettraledella Missione Applicativa (PRISMA) hyperspectral imagery (HSI) is a new era of space borne monitoring mission which was launched into orbit on 22 March 2019 with narrow bands (<10 nm) with capability across the full optical range (400–2500 nm) covering the visible, near and the shortwave-infrared ranges (Gasmi et al., 2022). PRISMA is a push broom sensor that records 250 spectral bands. The swath of hyperspectral imagery is 30 km. The PRISMA system consists of two hyperspectral sensors has a spatial resolution of 30 m and an average spectral resolution < 10 nm. Hyperspectral sensors are important tools for the identification of an objects and phenomena based on their high spectral resolution capability. PRISMA reflectance data were processed using the Spectral Hourglass Wizard (SHW) module available in ENVI software. SHW performs Minimum Noise Fraction (MNF), Data Dimensionally Determination, Pixel Purity Index (PPI), Derive Endmember and

Spectral Angle Mapper (SAM) for classification. The reference spectra of different crop types: maize, sunflower, moong sugarcane, chilli, rice and other spectra of water and built-up were derived from PRISMA hyperspectral imagery data.

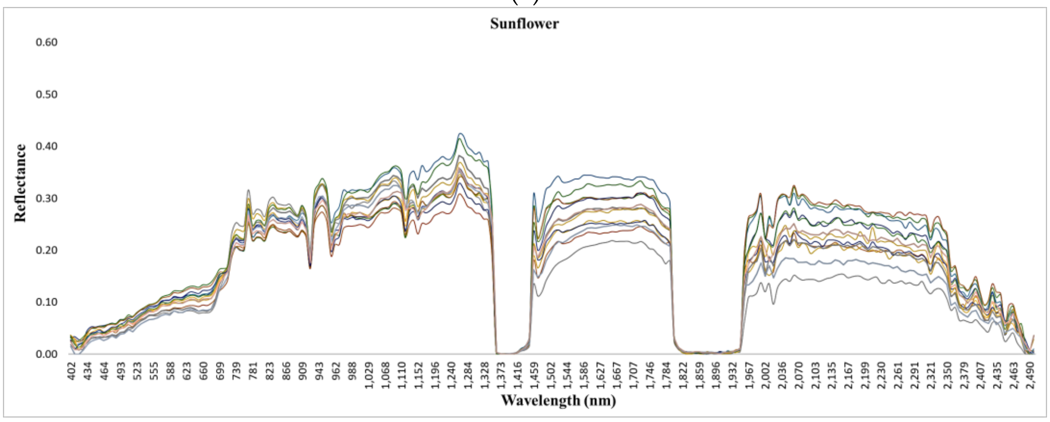
4. Results and Discussion

This study used PRISMA hyperspectral imagery derive spectral library of each crop type which covering over a part of Khanna, Amloh, Bassi, Pathanan which lies in Punjab state, India. Hyperspectral imagery data have been collected on dated 05 to 06 June 2022 for crop discrimination and analysis over study region. Hyperspectral sensors are more useful for distinguishing narrow spectral features, and such sensors can be separate out a large number of crop classes. Crop type's discrimination is an important requirement for crop mapping and monitoring. PRISMA hyperspectral data was processed based on spectral features and respective crop types were discriminated. The analysis of the PRISMA hyperspectral imagery was mainly focused on visible and near infrared bands of reflectance spectra to accurately discriminate and mapped the spatial distribution of crop types. Spectrum allows us to study very specific characteristics of agricultural crops. Spectral discrimination of agricultural crop types in complex environments is challenging as different crop types may have similar spectral characteristics, alternatively they may show different spectral signatures. The data was acquired using 234 spectral bands between 400 to 2500 nm. Such huge number of spectral bands increases our ability to identify each crop type spectral signature. The spectral dimension of remotely sensed data is the key control of the types of information able to be measure, classifying and mapping crop types.

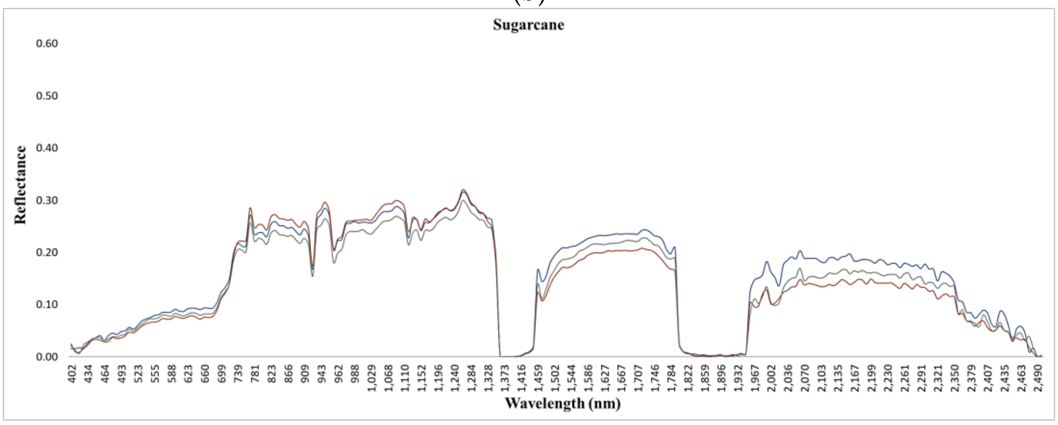
This research is mainly focused on development of crop spectral library, varying spectral response and interpretation of spectral features using different indices. Field data has been collected on the same time during the satellite imagery data. During the ground survey five different crop types' data (maize, moong, sugarcane, sunflower and chilli) and six other features data (fellow land, cultivated land, built-up, tree cover, water and algal bloom) have been collected over 135 sites. Field data collection sites were selected by visual inspection of crop types and other features present in the hyperspectral imagery data covering the study area and collected reflectance of each crop and other feature types. In this manner 43 spectral information's of five crop types and 38 spectral information of seven other features have been obtained (Figure 3). The substrates reflectance was calculated as a ratio of radiance from substrates against the downwelling irradiance. The collected end-member spectra of same crop types at different sites over study area were averaged to produce reference spectra for various specimens (Figures 4 and 5). The number of collections of spectral signatures of each crop is made to ensure the homogeneity of crop. The main reason for using average spectra is that same substrate types show variation in spectral reflectance in both magnitude and shape. The average spectral reflectance of each class was carried out in a full optical spectra range from 402 to 2497 nm with 9.0 nm interval. The sampling interval is 8.3 nm at the spectral range (402 to700 nm) while it is 9.1 nm at the spectral range (701 to 2497). The spectral bands between 730 to 1295 nm is optimal to identify maize crop while three spectral bands between 402 to 719 nm, 1448 to 1533 nm and 1949 to 2349 nm were used to identify rice crop. Crop type's discrimination is an important requirement for mapping and monitoring crops. Two major contributions in a crop reflectance spectrum are the leaf optical properties and the canopy structure. The narrowband spectral indices were significantly proven effective outcomes for crop pigments analysis.


Moong
Reflectance
0.60
0.50
0.40
0.30
0.20
0.10
0.00
Wavelength (nm)

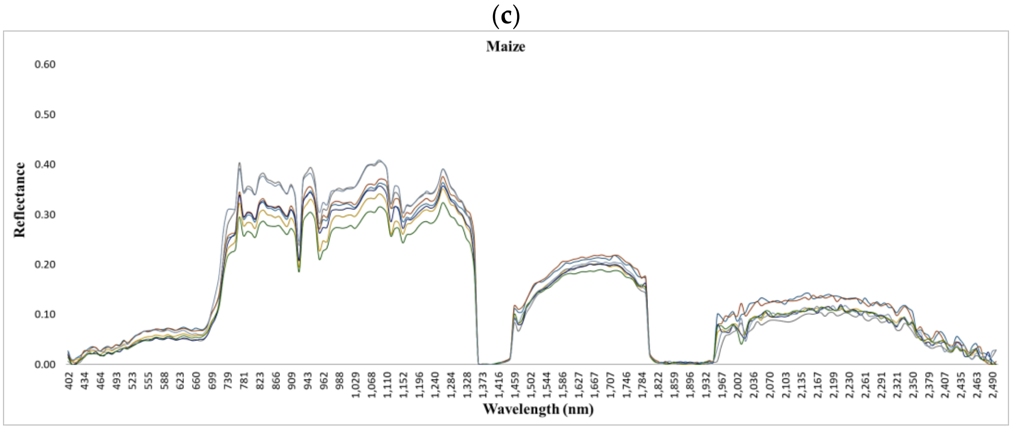
(**a**)


Sunflower
Reflectance
0.60
0.50
0.40
0.30
0.20
0.10
0.00
Wavelength (nm)

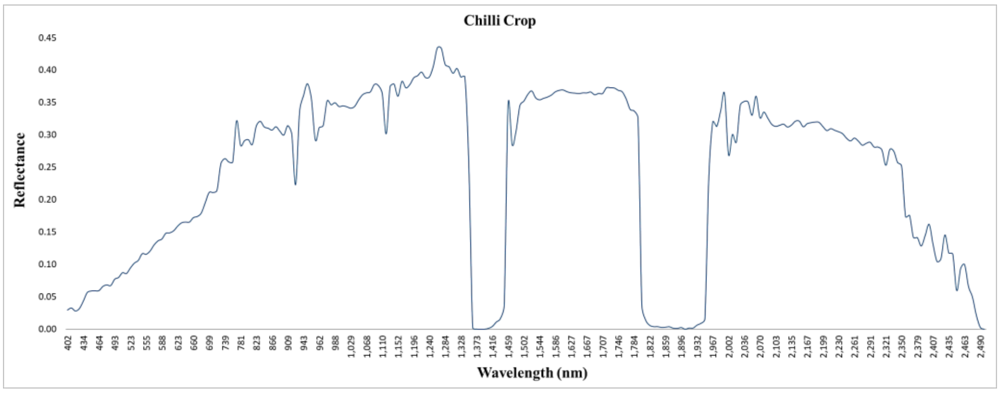
(**b**)


Sugarcane
Reflectance
0.60
0.50
0.40
0.30
0.20
0.10
0.00
Wavelength (nm)

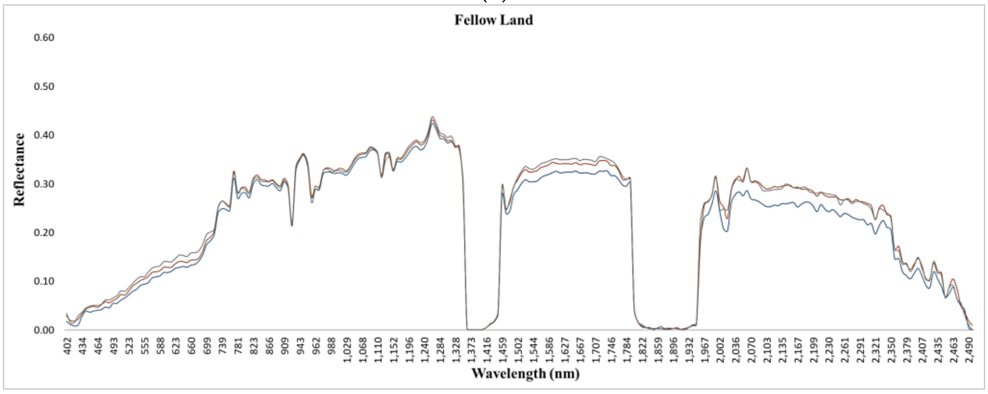
(**c**)


Maize
Reflectance
0.60
0.50
0.40
0.30
0.20
0.10
0.00
Wavelength (nm)

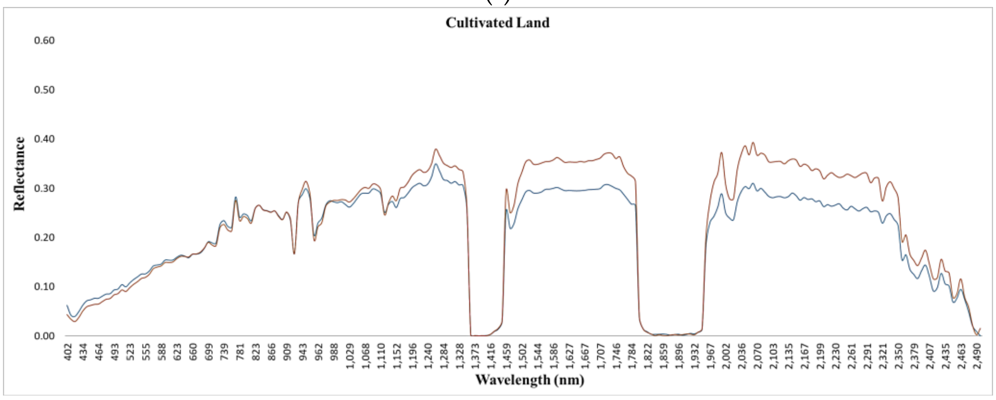
(**d**)


Chilli Crop
0.45
0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
Reflectance
402 434 464 493 523 555 588 623 660 699 739 781 823 866 909 943 962 988 1,029 1,068 1,110 1,152 1,196 1,240 1,284 1,328 1,373 1,416 1,459 1,502 1,544 1,586 1,627 1,667 1,707 1,746 1,784 1,822 1,859 1,896 1,932 1,967 2,002 2,036 2,070 2,103 2,135 2,167 2,199 2,230 2,261 2,291 2,321 2,350 2,379 2,407 2,435 2,463 2,490
Wavelength (nm)

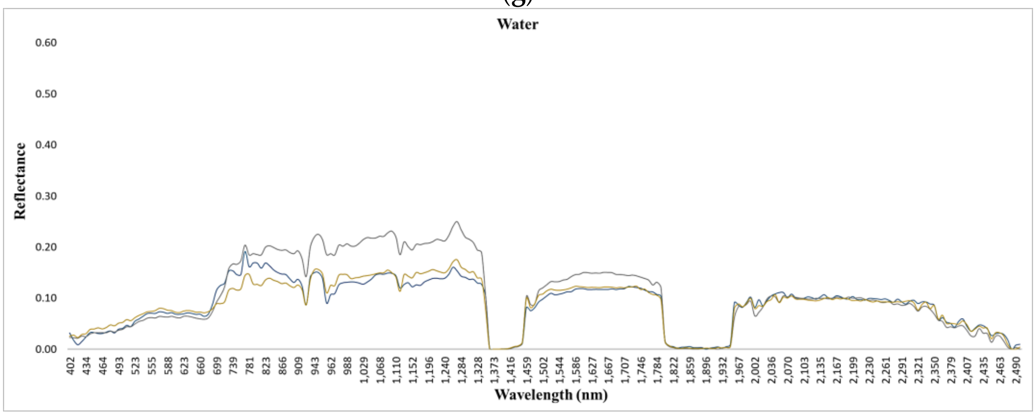
(**e**)


Fellow Land
0.60
0.50
0.40
0.30
0.20
0.10
0.00
Reflectance
402 434 464 493 523 555 588 623 660 699 739 781 823 866 909 943 962 988 1,029 1,068 1,110 1,152 1,196 1,240 1,284 1,328 1,373 1,416 1,459 1,502 1,544 1,586 1,627 1,667 1,707 1,746 1,784 1,822 1,859 1,896 1,932 1,967 2,002 2,036 2,070 2,103 2,135 2,167 2,199 2,230 2,261 2,291 2,321 2,350 2,379 2,407 2,435 2,463 2,490
Wavelength (nm)

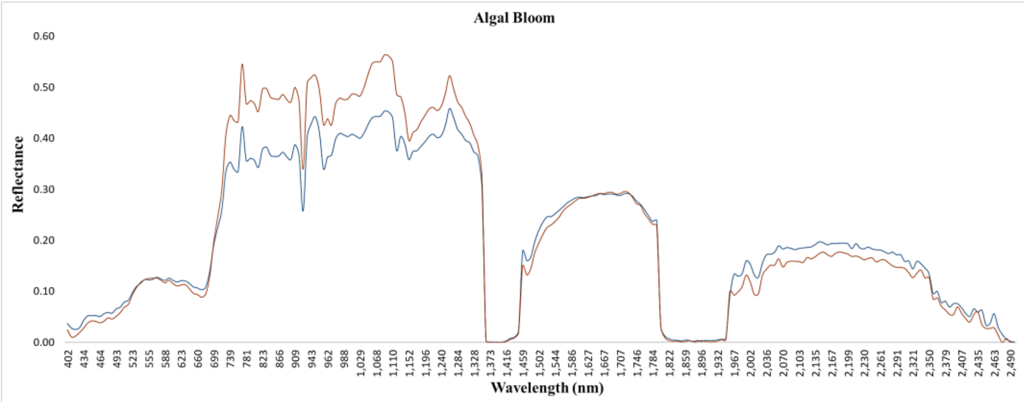
(**f**)


Cultivated Land
0.60
0.50
0.40
0.30
0.20
0.10
0.00
Reflectance
402 434 464 493 523 555 588 623 660 699 739 781 823 866 909 943 962 988 1,029 1,068 1,110 1,152 1,196 1,240 1,284 1,328 1,373 1,416 1,459 1,502 1,544 1,586 1,627 1,667 1,707 1,746 1,784 1,822 1,859 1,896 1,932 1,967 2,002 2,036 2,070 2,103 2,135 2,167 2,199 2,230 2,261 2,291 2,321 2,350 2,379 2,407 2,435 2,463 2,490
Wavelength (nm)

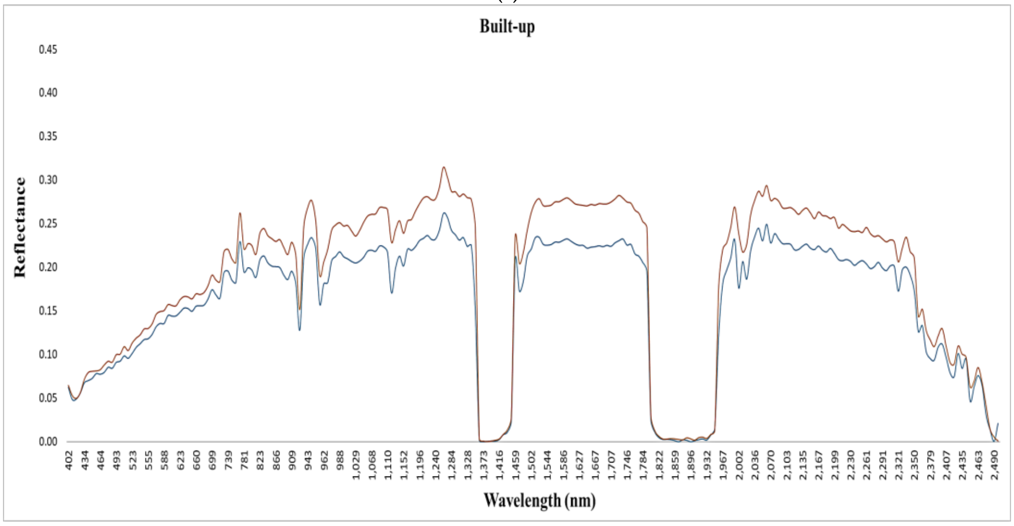
(**g**)


Water
0.60
0.50
0.40
0.30
0.20
0.10
0.00
Reflectance
402 434 464 493 523 555 588 623 660 699 739 781 823 866 909 943 962 988 1,029 1,068 1,110 1,152 1,196 1,240 1,284 1,328 1,373 1,416 1,459 1,502 1,544 1,586 1,627 1,667 1,707 1,746 1,784 1,822 1,859 1,896 1,932 1,967 2,002 2,036 2,070 2,103 2,135 2,167 2,199 2,230 2,261 2,291 2,321 2,350 2,379 2,407 2,435 2,463 2,490
Wavelength (nm)

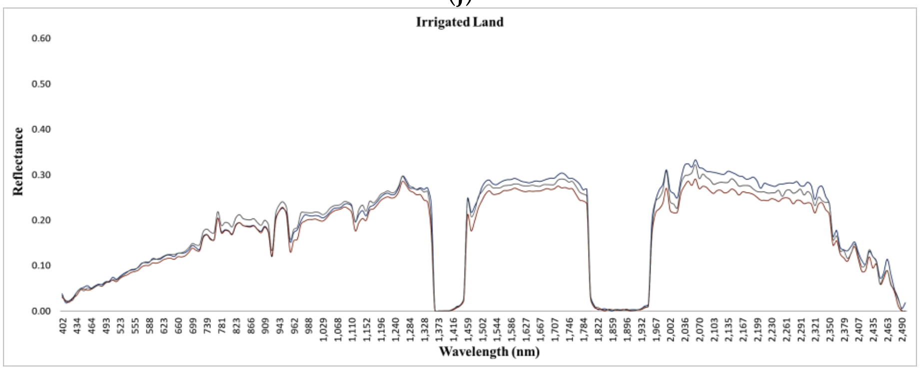
(**h**)


Algal Bloom
Reflectance
0.60
0.50
0.40
0.30
0.20
0.10
0.00
Wavelength (nm)

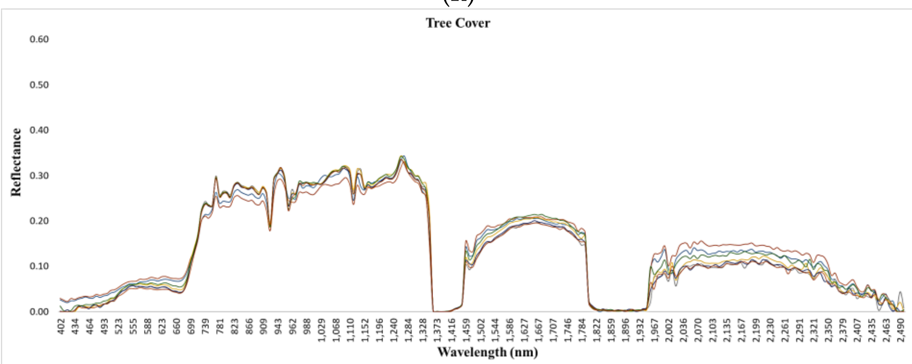
(**i**)


Built-up
Reflectance
0.45
0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
Wavelength (nm)

(**j**)


Irrigated Land
Reflectance
0.60
0.50
0.40
0.30
0.20
0.10
0.00
Wavelength (nm)

(**k**)


Tree Cover
Reflectance
0.60
0.50
0.40
0.30
0.20
0.10
0.00
Wavelength (nm)

(**l**)

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.

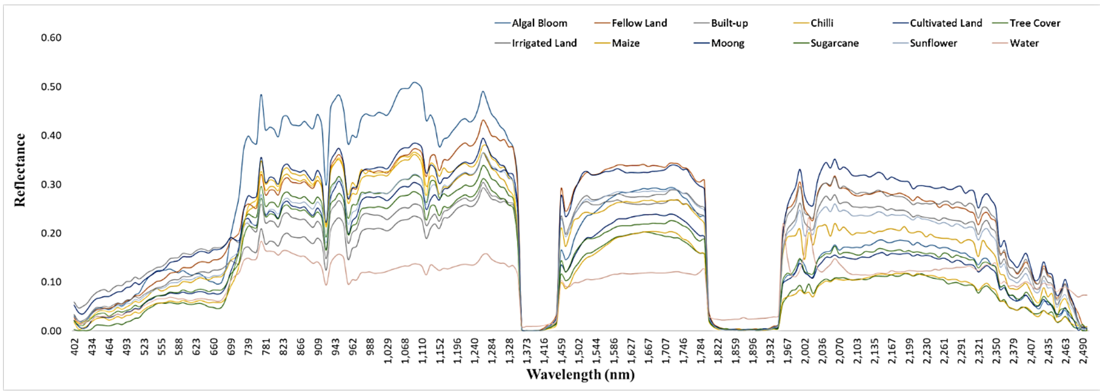


Figure 4. Average reflectance spectra of crop types and other features at different sites across the study area.

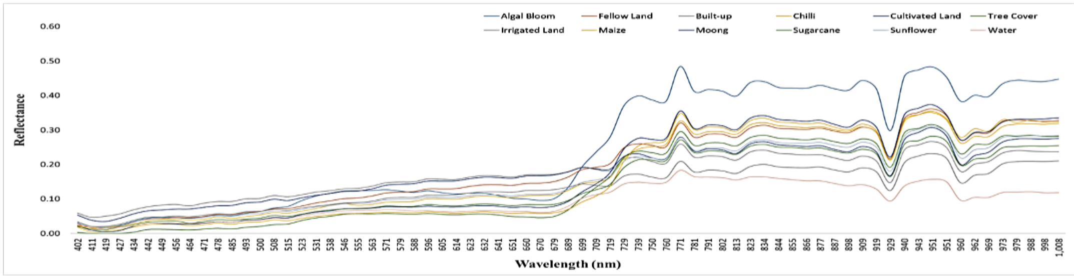


Figure 5. Average reflectance spectra of crop types and other features in the spectral range of 400–1000 nm across the study area.

Hyperspectral sensors acquire reflectance values of each crop types at many different wavelength bands and are particularly sensitive to changes in the chlorophyll content and the structural properties of canopies. Reflectance pattern showed the same trend for all five crops, however reflectance of Chilli was higher than other crops along the whole spectrum. The highest spectral reflectance was shown in infrared spectral zone (940 to 1300 nm), relatively low reflectance in the spectral zone (1361 to 1449 nm and 1822 to 1932 nm) while the lowest reflectance was found in the spectral zone (2350 to 2495 nm). This study observed that there is a big similarity in the spectral reflectance pattern in all crop types and it is very difficult to discriminate them. The visible region of the crop reflectance spectrum is characterized by low reflectance due to strong absorption by pigments like chlorophyll. The chlorophyll has strong reflectance peaks in the red and blue wavelength region. Blue peak is not used to estimate the chlorophyll content because it overlaps with the absorbance of the carotenoids. Maximal absorbance in the red region occurs between 660 nm and 680 nm. The transition from visual to infrared is characterized by a steep increase in reflectance referred to as the red-edge. This edge and the subsequent plateau are related to the leaf chlorophyll content and to the canopy structure. The discrimination information between crop types to be characterized by the height of the visible spectrum (400 to 650 nm), the location of the red edge (700 nm) and the height of the infrared spectrum (750 to 900 nm). NIR spectral zone is the best to differentiate between these six crops while visible spectral zones did not show any significant difference in the crop reflectance. The wavelength ranges 400 nm–800 nm was used for crop health analysis. This study showed that NIR spectral zone is the best spectral zone to differentiate each crop types. The spectral library of crop types can be useful for a better understanding of the image classification problems. Many study revealed that spectral reflectance of vegetation from

400 to 700 nm region is primarily governed by the abundance of chlorophyll and other pigments (Wu et al., 2008). The hyperspectral data contains spectral responses of crop leaves in the ripening stage for extraction of chlorophyll, carotenoid and xanthophyll contents.

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. Conclusions

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.

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

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

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