COMPARISON OF CROP DISCRIMINATION USING AVIRIS-NG AND LISS-IV DATA OVER HETEROGENEOUS AGRICULTURAL PATCHES

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ABSTRACT
Crop mapping and discrimination provide an important basis for many agricultural applications such as acreage, biomass, yield, crop rotation and soil productivity. Remote sensing data, methods and approaches provide the best options for large area agricultural cropland characterization for precision agricultural management practices by accurately mapping of crop type and yield indicators. Traditional multispectral broadband sensor data have known limitations of sensor saturation and absence of specific narrow bands to target and highlight specific biophysical and biochemical characteristics according to crop type. These factors lead to significant uncertainties in the discrimination of crop type. Recent advances in hyperspectral remote sensing technology provide the opportunity to measure the response of different crop type in terms of morphological and physiological characteristics. The specific narrow bands have a capability to perform crop discrimination over homogeneous and heterogeneous agricultural areas. The continuous band spectrum from imaging spectroscopy have opened up new avenues in the field of classification. In this study, crop discrimination has been carried out using principal component analysis and supervised classification techniques such as maximum likelihood classification (MLC) and spectral angle mapper (SAM) algorithms. In this study, AVIRIS-NG airborne hyperspectral data acquired on Maddur, Karnataka and equivalent multispectral LISS-IV data convolved through three broadband regions (Green: 0.52-0.59 nm, red: 0.62-0.68 nm, near-infrared: 0.77-0.86 nm) using spectral response function of Resourcesat-2 (RS-2) LISS-IV, were used over mixed and heterogeneous agricultural area of Maddur, Karnataka in Berambadi watershed located in Kabini river basin. The dominant soil types were red and black soils. Data dimensional reduction has been carried out using principal component analysis. *In situ* crop information were used to perform SAM and MLC-based classification. Classification accuracy was computed using confusion metrics. SAM classification showed classification accuracy of the order of 77.7 % and 42.8% with Kappa coefficient of 0.75 and 0.34 for AVIRIS-NG and LISS-IV equivalent, data, respectively. The MLC-based classification showed accuracy of 94.3% and 55.6% and Kappa coefficient of 0.93 and 0.46 for AVIRIS-NG and LISS-IV data. It can be concluded that imaging hyperspectral narrowband data has the potential to discriminate crops in a mixed and heterogeneous crop cluster with higher accuracy as compared to equivalent resolution multi-spectral broadband data.

INTRODUCTION
The blooming population around the globe and depleting natural resources are constant threats to global food security. To ensure the food security and nutritional requirements for rapidly growing population, precise and efficient management of agricultural resources is the need of time. Precision agricultural management involves many important factors like cropland characterization, crop type discrimination, cropping system management, biomass and yield monitoring and quantification of various biophysical and biochemical agricultural parameters. Accurate and efficient cropland characterization and crop type discrimination plays key role for many agricultural applications such as acreage, biomass, yield, crop rotation and soil productivity. The development of precision agricultural practices has fueled the need of advance remote sensing techniques for more accurate and cost effective cropland characterization and crop type discrimination (Alchanatis and Cohen, 2011; Thenkabail, 2003). Multispectral satellite technologies have been commonly used for various agricultural applications (Ferrato and Forsythe, 2013). In a single observation, multispectral sensors generate three to six spectral bands of data that range from visible to near infrared (NIR) portion of the electromagnetic spectrum(Ferrato and Forsythe, 2013; Rahul et al, 2017). These traditional multispectral broadband sensor data have known limitations of sensor saturation (Thenkabail, Enclona, Ashton, Legg and Van Der Meer, 2004). These multispectral sensors are unable to provide specific agricultural parameters due to absence of specific narrowbands to target and highlight specific biophysical and biochemical parameters (Gitelson, 2011; Gitelson, Gritz, & Merzlyak, 2003). All these limitations result into significant uncertainties in spectro-biochemical/biophysical modeling of agricultural crops. Agricultural crops are significantly better characterized, classified, modeled and mapped using hyperspectral remote sensing data (Thenkabail et al., 2012). Hyperspectral sensors commonly collect more than 200 narrow contiguous spectral bands that range from the visible to shortwave infrared section of the electromagnetic spectrum (Ferrato and Forsythe, 2013; Rahul et al., 2017). The continuous availability of hyperspectral imagery, which records hundreds of image corresponding to different wavelength channels has opened new avenues in the field of crop type discrimination,

yield, biomass and area estimation and various biophysical and biochemical parameters estimation (Asner, 1998; Thenkabail et al., 2011). The need of targeting specific narrowbands to study the spectral properties of agricultural crops is obvious due to the molecular composition of the plant material which reflects, absorbs and emits electromagnetic energy at specific wavelengths and with distinct patterns (Mariotto et al., 2013). Many studies have been conducted on a wide array of crops and their variables such as crop type discrimination, yield, chlorophyll a and b, total chlorophyll, nitrogen content, carotenoid pigments, plant stress, plant moisture, above ground biomass and biophysical variables (Boyd and Ripple, 1997; Boyd et al., 1999). Through these studies it has been shown how hyperspectral data can provide significant improvements in spectral information content when compared with the broadbands in modeling biophysical and yield characterization of agricultural crops (Thenkabail et al., 2000; Thenkabail, Smith & De-Pauw, 2002), measuring chlorophyll content of plants (Blackburn and Ferwerda, 2008), sensing subtle variations in leaf pigment concentrations (Blackburn and Ferwerda, 2008), extracting biochemical variables such as nitrogen and lignin (Houborg and Boegh, 2008), detecting crop moisture variations (Colombo, Busetto, Meroni, Rossini, & Panigada, 2011), assessing absolute water content in plant leaves (Jollineau & Howarth, 2008), identifying small differences in percent green vegetation cover (Chen, Wang, & Wang, 2008), detecting plant stress (Thenkabail, Enclona, Ashton and Van Der Meer, 2004), discriminating land-cover types (Thenkabail, Enclona, Ashton, Legg, et al., 2004). These studies have made significant advances in crop type discrimination, understanding, modeling, and mapping various biophysical and biochemical quantities of agricultural crops (Mariotto et al., 2013).As discussed above, crop area is important for government and economic players. The first step for such precision agricultural practices using hyperspectral remote sensing data is the crop type discrimination. Crop type discrimination using hyperspectral remote sensing data is a challenging task due to the spectral similarities between the crops (Cai et al., 2009). There are many factors which significantly affect crop type discrimination like crop physiology, crop phenology, crop rotation, crop calendar and regional aspects. Given the above background, the primary objective of this study is establishing a common methodology of crop type discrimination using hyperspectral and multispectral remote sensing data and to establish the advantages of hyperspectral data over traditional multispectral data. In this study, AVIRIS-NG airborne hyperspectral data and Resourcesat-2, LISS-IV equivalent multispectral data is used to perform crop type discrimination (Rahul et al, 2017). The outcome of this research will help establish the common methodology to perform crop type discrimination using hyperspectral and multispectral data. It will also establish the shortfalls of multispectral data and advantages of hyperspectral data over multispectral data.

STUDY AREA AND DATA USED

The study area chosen to conduct the study was Maddur, Chamarajanagar, Karnataka. Maddur was located in Gundlupet tehsil of Chamarajanagar district in Karnataka, India. Maddur was situated 16 km away from sub-district headquarters Gundlupet and 52 km away from district headquarters Chamarajanagar. Chamarajanagar has moderate climate and it falls in the southern dry agro climatic zone of Karnataka. In this district, summers are fairly hot and winters are cold. Overall, the average maximum temperature in the district is 34°C and the average minimum temperature is 16.4°C. In the morning, relative humidity ranges from 69 to 85 % and in the evening it ranges from 21 to 70 % (Rahul et al., 2017). Maximum rainy days are observed in Gundlupet with 73 days in the season with average rainfall of 731.80 mm yearly (Rahul et al., 2017). Reddish brown forest soil, yellowish grey to greyish sandy loam soils and mixed soils are major soil types observed. Major crops are paddy, ragi, sorghum, jower, maize, gram, tur, other pulses, sunflower and other oilseeds and vegetables.During the field campaign of AVIRIS-NG crops like cotton, field beans, horsegram, tomato, turmeric, pulses, maize, beans, cabbage, carrot, banana, chili, brinjal sugarcane, beetroot, garlic and potato were observed. In this study for crop discrimination, ground based hyperspectral data collected during AVIRIS-NG field campaign and airborne hyperspectral imagery of AVIRIS-NG are used. During the field campaign, locations of various crops were recorded using hand help GPS. Region of interest were retrieved from these locations for each and every crop (Rahul et al., 2017).

METHODOLOGY

Pre-processing of AVIRIS-NG data and image generation equivalent to LISS-IV

Crop locations were collected for various crop type during the *in situ* data collection campaign conducted during AVIRIS-NG flight time. Based on the GPS locations of different crops region of interest were retrieved to perform crop type discrimination. To generate LISS-IV equivalent multispectral image relative response function of RS-2 LISS-IV was applied over AVIRIS-NG hyperspectral data. Application of relative response function resulted in to image having three bands equivalent to LISS-IV multispectral data.

Principal Component Analysis, Spectral Angle Mapper and Maximum likelihood classifier

Hyperspectral imaging can overcome many limitations of multispectral data by distinguishing various spectral signature of land use land cover. The hyperspectral data contains contiguous, narrow spectral band that lead to data redundancy and high data dimensionality. Hence, hyperspectral data analysis and image processing involves critical attention to data compression. Reduction in data redundancy and dimensionality leads to higher classification accuracy and reduction in data volume. Principal components analysis (PCA) is a general tool used for reducing data dimensionality in remote sensing image processing. The process of PCA can be divided into following three steps:

1. Calculation of the covariance matrix of multi-band images.
2. Extraction of the eigenvalues and eigenvectors of the matrix.
3. Transformation of the feature space coordinates using these eigenvectors.

Here, PCA was applied to AVIRIS-NG hyperspectral data and LISS-IV equivalent multispectral data and based on the maximum variance first five principal components (PCs) of AVIRIS-NG data and first two PCs of LISS-IV equivalent data were selected. Using ROIs based on the *in situ* crop locations, supervised classification technique spectral angle mapper was appliedover AVIRIS-NG data and LISS-IV equivalent data. SAM defined the spectral similarity between two spectra by calculating the angle between the spectra, treating them as vectorsin a space with dimensionality equal to the number of bands. SAM compared the angle between the spectrum vector of known class and each pixel vector of unknown class in the n-dimension space where n is the number of spectral bands.In the classification, the class with the smallest angle was assigned to the corresponding image pixel.The angle α between the test spectrum and the reference r is calculated as

$$\cos^{-1}\left(\frac{\left(\sum_{i=1}^{nb} t_i r_i\right)}{\sqrt{\sum_{i=1}^{nb} t_i^2}\sqrt{\sum_{i=1}^{nb} r_i^2}}\right) \qquad (1)$$

Where,
nb= Number of bands in the image
t= Test Spectrum
r= Reference Spectrum
α= Spectral Angle

In this study, Single threshold value, 0.1 radian was given to all the classes. The maximum acceptable angle between the test spectrum vector and the pixel vector was 0.1 radian. Another supervised classification method maximum likelihood classification (MLC) was used in this study for crop discrimination. This technique was based on the conditional probabilities and these conditional probabilities were used to develop the maximum likelihood decision rule.The flow of methodology is given in Figure 1. Post classification accuracy was computed using statistical technique confusion matrix.

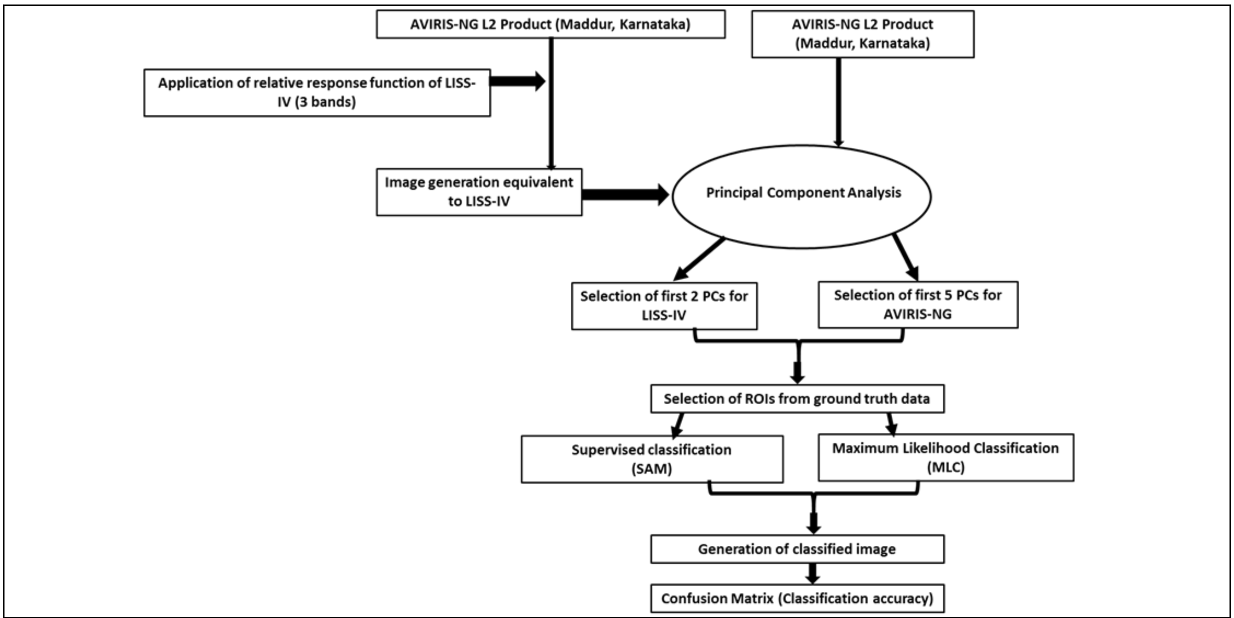

Figure1. Flow Of Methodology For Classification

RESULTS

Crop type discrimination was performed using aforementioned techniques where PCA was used to reduce data redundancy and dimensionality. PCA was applied to AVIRIS-NG hyperspectral data and LISS-IV equivalent multispectral data. First five and two PCs from AVIRIS-NG and LISS-IV data respectively were used for crop classification over the same region. The spatial variability of selected PCs for AVIRIS-NG and LISS-IV are shown in Figure 2. The five PCs from AVIRIS-NG showed better variability as compared to LISS-IV. Based on the ground observation points, ROIs were extracted to apply in spectral angle mapper classification algorithm. SAM algorithm determines the spectral similarity between two spectra by calculating the angle between them as vectors in a space with dimensionality equal to the number of bands (n). SAM compares the angle between the reference spectrum and test spectrum in n-dimension space. Smaller angle represents closer matches to the reference spectrum. Crop discrimination was successfully achieved through spectral angle mapper over AVIRIS-NG data. Figure 3 showed classified image of AVIRIS-NG data where the field crops were discriminated based on the ground truth ROIs. However, crop discrimination in LISS-IV equivalent multispectral data in Figure 4 indicated misclassification due to the absence of specific narrow bands to target and highlight specific biophysical and biochemical characteristics according to the crop type.

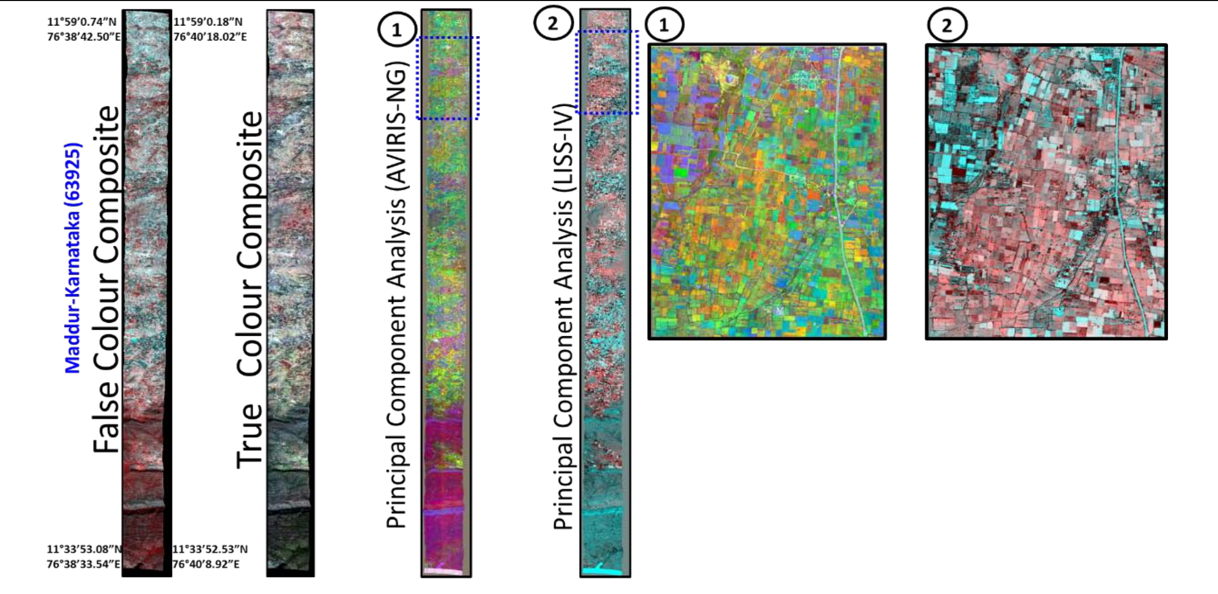

Figure 2. Principal Components Analysis Using AVIRIS-NG And LISS-IV Data

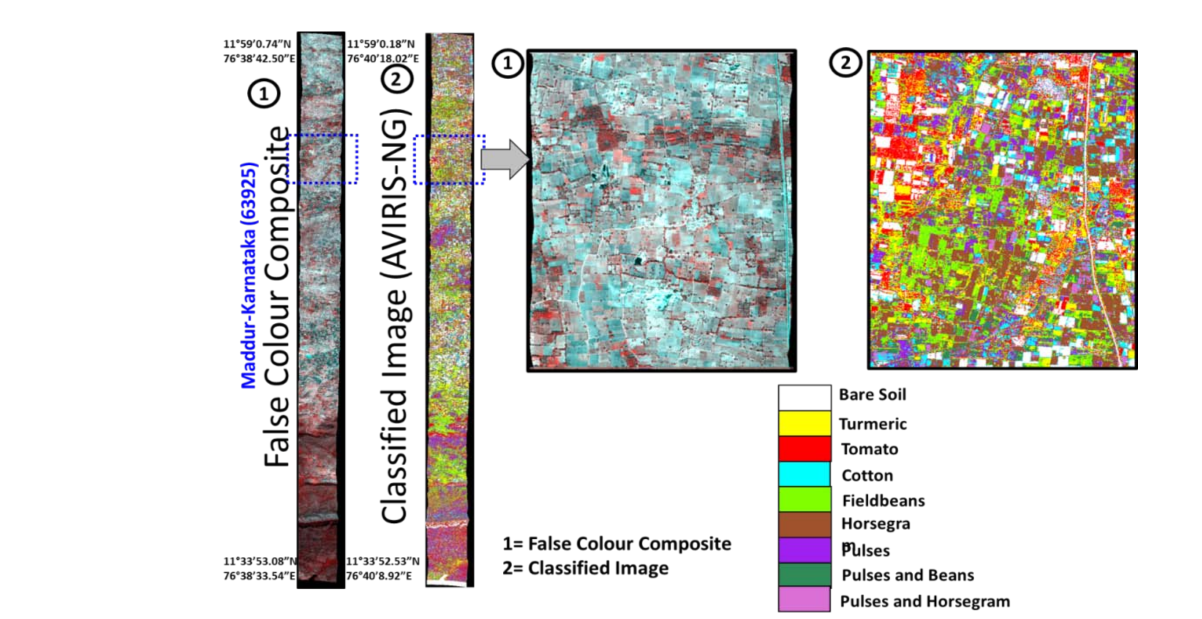

Figure 3. Crop classification using AVIRIS-NG data using spectral angle mapper algorithm

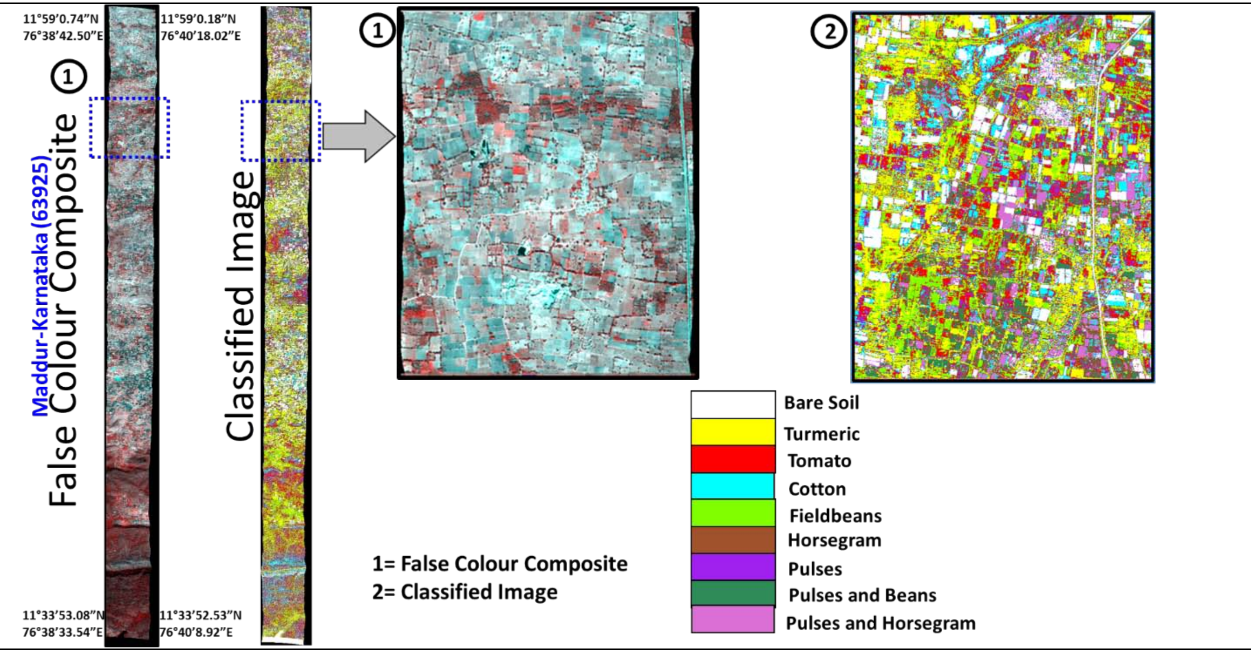

Figure 4. Crop Classification Using LISS-IV Equivalent Spectral Data Using Spectral Angle Mapper Algorithm

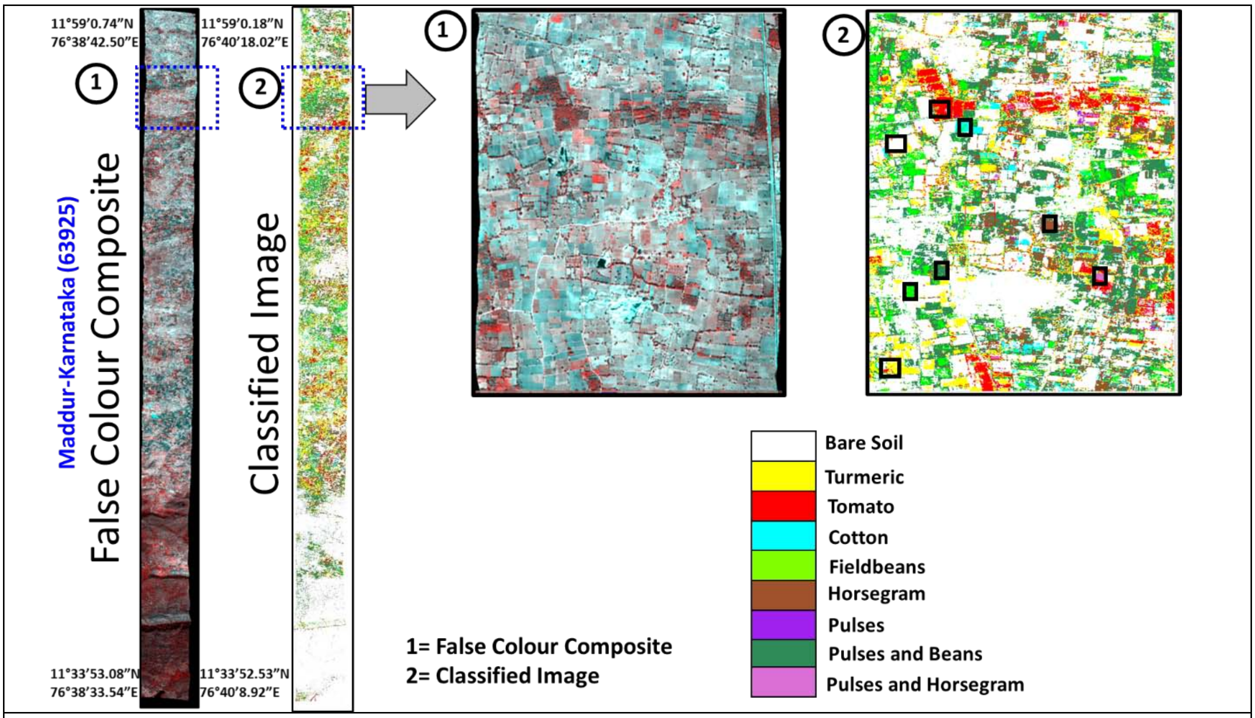

Figure 5. Crop Classification Using AVIRIS-NG Data Using Maximum Likelihood Classification

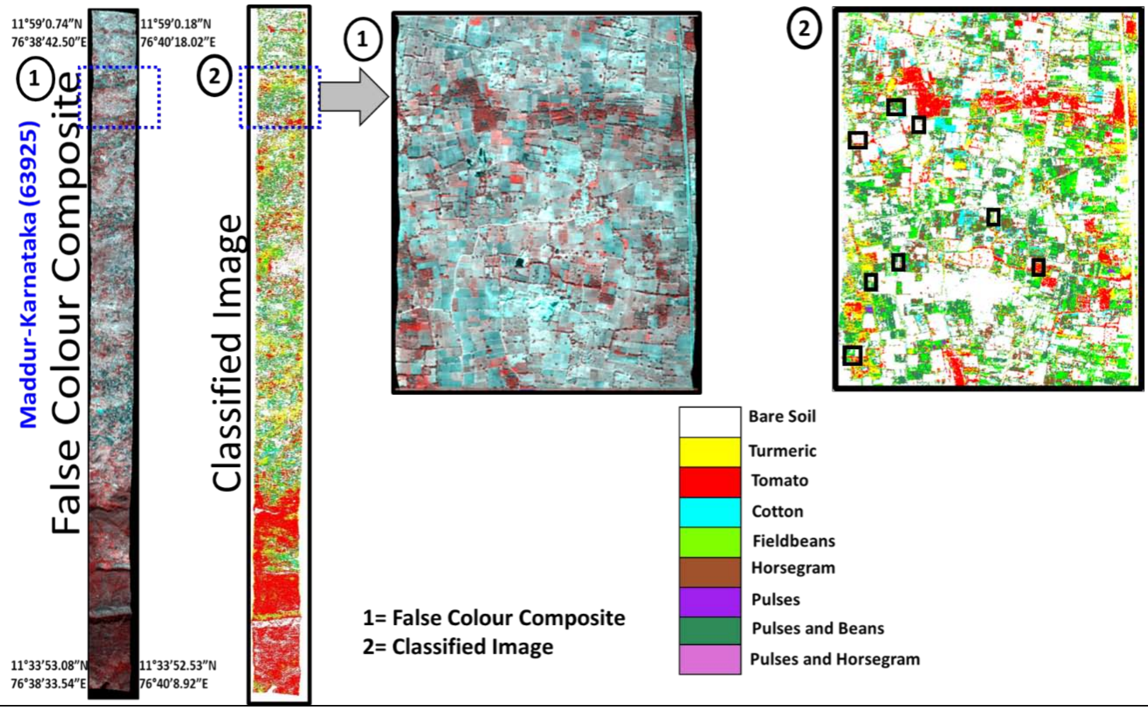

Figure 6. Crop Classification Using LISS-IV Equivalent Spectral Data Using Maximum Likelihood Classification

Maximum likelihood classification technique was also applied over AVIRIS-NG hyperspectral data and LISS-IV equivalent multispectral data for crop discrimination. This supervised classification technique is based on the conditional probabilities and these conditional probabilities are used to develop the maximum likelihood decision rule. Figure 5 represents successful crop discrimination achieved by applying MLC over AVIRIS-NG hyperspectral data. Whereas, figure 6 shows misclassification of crops due to loss of spectral information in LISS-IV equivalent multispectral data. The spectral resolution was the main factor that distinguishes hyperspectral imagery from multispectral imagery. Hyperspectral sensors contained bands with narrow wavelengths while multispectral sensors contained bands with broad wavelengths. The advantage of using hyperspectral data over multispectral data is the ability to define crop biophysical and biochemical parameters with a higher spectral resolution. Successful application of ground based crop and soil ROI over AVIRIS-NG hyperspectral data for crop discrimination proved strength of ground data. Major advantage of hyperspectral data is inferred that efficient crop discrimination is achieved over AVIRIS-NG hyperspectral data. MLC resulted in higher classification accuracy as compared to spectral angle mapper algorithm for both the data of AVIRIS-NG hyperspectral data and LISS-IV equivalent multispectral data. Using both the supervised classification methods higher classification accuracy was achieved for AVIRIS-NG hyperspectral data as compared to LISS-IV equivalent multispectral data. Classification accuracy was estimated by computing confusion matrix. For AVIRIS-NG hyperspectral data, overall classification accuracy was 77.7 % and kappa coefficient was 0.75 and for LISS-IV equivalent multispectral data overall classification accuracy was 42.8% and kappa coefficient was 0.34.

DISCUSSION

This study examined the performance of hyperspectral and multispectral remote sensing data using common methodology where three techniques (1) principal component analysis, spectral angle mapper and maximum likelihood classifier were implemented to perform crop type discrimination. PCA played two key roles in hyperspectral data analysis for this study. Best wavebands to perform crop classification were selected and redundant bands were removed using PCA. Through this process, we were left with best bands, able to eliminate redundant bands and helped to reduce the data volume. PCA transformed original hyperspectral data into a new coordinate system, which helped to find the information in the original intercorrelated variables into a few uncorrelated variables called principal components (PCs). Typically, first few PCs explained overwhelming proportion of variability (explained by eigenvalue) in data. Adjacent hyperspectral wavebands showed noise, saturation (explained by eigenvalue) and redundancy of the data. The original high dimension data then was transformed to a few bands that contained most of the information in the original bands. The importance of the hyperspectral wavebands in each PC was determined based on the magnitude of eigenvectors. Results typically demonstrated higher eigenvector of first few bands. Therefore, based on the analysis and variability of the data it was conferred that higher the eigenvector, higher the importance of the band. Thus, PCA helped in determining wavebands that had the greater influence in terms of variability and eigenvectors and redundant data in both hyperspectral and multispectral data. As shown in fig. 2, PCs of hyperspectral data showed the greater variability which is desirable to achieve crop type discrimination efficiently whereas PCs of multispectral data showed lesser variability which decreases the classification accuracy. Spectral angle mapper algorithm was used for crop type discrimination. Ground based crop ROIs were used as an input training data set.In SAM algorithm, each pixel was considered as an N-dimensional vector. Therefore, each vector defined a set of angles with the coordinates representing the band or features. In this algorithm, the angular distance between pixels was considered as the measure of distance. Each pixel was assigned to the class which was closest to it based on the angular distance.SAM was successfully applied due to its ability to handle high dimensional data and large number of pixels in training data set as it reduced the dimensionality to the axes. The main advantage of SAM was inferred that due to its insensitivity to the magnitude of the pixel vectors, only the angular distance between vectors were used in establishing crop classification. Therefore, it holds a special significance in classifying vegetation. As shown in fig. 3, SAM successfully discriminated crop type based on ground data ROIs. In case of multispectral LISS-IV data (fig. 4) significant amount of misclassification was observed due to the absence of specific narrow bands to target and highlight specific biophysical and biochemical characteristics according to crop type. Another supervised classification technique maximum likelihood classifier was applied over hyperspectral and multispectral data. This classifier performed based on the Bayes' classification rule which is based on the conditional probabilities of the pixel vectors. MLC estimates the conditional probabilities using training data and these conditional probabilities are used to develop the maximum likelihood decision rule. MLC resulted in higheraccuracy of classification than SAM classifier due to multivariate normal data distribution and adequate numbers of training pixels.Post classification, accuracy assessment was carried out by using confusion matrix. For AVIRIS-NG hyperspectral data, overall classification accuracy was 77.7 % and kappa coefficient was 0.75 and for LISS-IV equivalent multispectral data overall classification accuracy was 42.8% and kappa coefficient 0.34 achieved by spectral angle mapper classifier.With MLC, overall classification accuracy 94.3% and kappa coefficient 0.93 for AVIRIS-NG data and for MLC overall classification accuracy is 55.6% and kappa coefficient 0.46 is achieved.

CONCLUSION

In general, hyperspectral sensors provide significantly better classification results than multispectral sensors but their classification performance depends on other factors such as signal to noise ratio and adequate feature selection. The most important broad spectral intervals for crop type discrimination using imaging spectrometers are the NIR (760-900 nm), SWIR (1500-1750 nm), red (66-700 nm) and green (500-600 nm). A number of focused hyperspectral narrowbands help distinctly separate crop type based on their biophysical and biochemical properties. In this study, multispectral and hyperspectral data was used to discriminate crop type in heterogeneous agricultural area. PCA was utilized to establish data variability and reduce data redundancy. Supervised classification technique SAM algorithm was applied over AVIRIS-NG hyperspectral data and LISS-IV multispectral data. Better classification accuracy was achieved for AVIRIS-NG data. Narrow contiguous wavebands, specific wavebands corresponding to specific pin-pointing parameters for crops and continuous coverage of EM spectrum, all these numerous factors offered by hyperspectral data are of great advantage when compared with possibilities offered by broadband multispectral data.

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