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ORIGINAL ARTICLE

Mapping Mangrove Species Using Hyperspectral Data: A Case Study of Pichavaram Mangrove Ecosystem, Tamil Nadu

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Abstract

Background There are many studies on mangrove mapping, zonal demarcation, landuse and land cover changes, and also topics like its loss and restoration using multispectral data. In the recent past, advanced remote-sensing data have been used for species discrimination, mapping, etc.

Purpose The current research aims at identifying and mapping mangroves species along Pichavarm coast of Tamil Nadu, India, using hyperspectral remote-sensing data. The study attempts to map the species by generating the reference spectra from the existing reports and research papers, as surrogate to expensive field work in conjunction with Hyperion data of January 2013.

Methods Image was pre-processed followed by Minimum Noise Fraction (MNF) and Pixel Purity Index (PPI). The output of MNF and PPI has been analysed by visualizing it in n-dimensions for end-member extraction. There were eleven spectra taken from the end-members, which were matched with reference spectra.

Results The spectra—matched—, have been used as an input for classification of data with classifiers like Spectral Angle Mapper (SAM), Spectral Feature Fitting (SFF) and Spectral Information Diversion (SID) to identify and map mangroves species. Further to monitor the exact presence of the species at sub-pixel level, linear spectral un-mixing (LSU) was also performed.

Conclusions The study found SAM with LSU as the best approach for mangrove species mapping in Pichavaram coast.

Keywords Spectral Angle Mapper (SAM) · Spectral Feature Fitting (SFF) and Spectral Information Diversion (SID) · Linear Spectral Un-mixing (LSU) · Hyperion · Minimum Noise Fraction (MNF) and Pixel Purity Index (PPI)

1 Introduction

Mangroves, the intertidal halophytic vegetation, show the unique characteristics of adaptation to saline conditions and form a special vegetation zone lining the coastal areas (Lugo and Snedaker 1974; Tomlinson 1986). They play a major role in maintaining the global carbon cycle by sequestering high rates of carbon compared to other terrestrial forest types, apart from their invaluable socio-ecological services (Prasad et al. 2017). They are observed along the coastal areas of tropical and sub-tropical regions lying between 30°N and 30°S Latitude (Giri et al. 2011; Sheridan and Hays 2003) and occupy about 15 million hectares worldwide (Ghosh et al. 2015). Within India, mangroves cover an area of 4740 km^2 (SFR 2015) and are found in nine coastal states and three union territories of the country with high percentage of cover in Sundarbans, Gujarat and Andaman and Nicobar islands (44, 23 and 13% respectively) (Kandasamy 2017).

Mapping and monitoring of these fragile ecosystems are important in the context of their unique biodiversity as well as services and products (Prasad et al. 2010). Since traditional methods are difficult and time consuming, researchers have opted remote sensing satellite data to map mangroves globally (Kuenzer 2011). The utility of coarse and moderate resolution multispectral satellite data helped in mapping areal extent of mangroves. However, while using multispectral data, one must compromise with the

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classification results that show small patches of mangrove having multiple species or same species due to low spatial resolution of multispectral data (Marshall 1994). Further mapping the mangrove forest at species level is very much needed to understand existing biodiversity and also for the management (Kuenzer 2011). In fact, identification and differentiation of the mangrove species and understanding the local situation in and around mangrove areas in the image are difficult. Towards this, ground survey activities help to verify and calibrate the analysis that is derived from the satellite images (Green 1998). However, frequent intensive field work is practically difficult and often it is pretty impossible in inaccessible areas within the mangrove ecosystem (Green 1998).

The advent of hyperspectral, high spatial resolution satellite data along with digital elevation models made it possible to map mangrove species accurately (Mesta et al. 2014; Kamal and Phinn 2011; Adam et al. 2010; Rodriguez and Feller 2004; Hirano et al. 2003). The prospective of hyperspectral remote sensing is to store data in hundreds of contiguous narrow bands which provide useful information to assess, enhance and discriminate individual features. This greatly increases the level of detail by a complete spectrum of a feature (Folkman 2001) However, it is very difficult to extract, analyze or classify hyperspectral satellite data without the proper image processing algorithm, owing to its high dimensionality (Green 1998). High dimensionality challenges the precision of the estimates of class distribution like the mean and the covariance in the feature space. This complex phenomenon is termed as "the curse of dimensionality" which results in low output accuracy as it has an imprecise class estimates (Green 1998). To avoid this complexity and for better results, more training samples are given to the class models, which means immense field survey is required. This will practically increase the cost of the ground truth. However, classification of satellite data can be done with the available reference reports provided they have geo-coordinate information about the features for selection and extraction of signatures from satellite data. This will certainly replace the expensive field work (Green 1998).

In view of this context, the current study demonstrates mapping mangrove species using hyperspectral data by implementing the classification techniques, such as Spectral Angle Mapper (SAM), Spectral Feature Fitting (SFF), Spectral Information Diversion (SID), and differentiate the mixed pixels using linear un-mixing without field inventory dataset or lab tests. The study used reference data from literature depicting the geographical coordinates (latitude–longitude) of the individual species to extract and identify mangrove species from hyperspectral data and further to map them. This is a trial attempt to check whether mapping of species can be done in the absence of field data and with help of available literature and reports.

2 Study Area

Pichavaram is an estuarine mangrove in the south east coast (79°45–79°52′E and 11°22′–11°30′N) of Tamil Nadu state, India, with reserve forest status declared on 11th February 1893 (Sandilyan 2009). It falls under Viluppuram forest division of Tamil Nadu and is observed between northern Vellar and southern Coleroon estuarine systems forming a complex of Vellar–Coleroon estuary complex (Jayanthi 2001). It is the second largest mangrove in India (Sandilyan 2009; Gupta and Shaw 2013) with an area of 1357 hectares and is characterized as river-dominated mangrove ecosystem (Kandasamy 2017). The mangrove constitutes three reserve forests Killai, Pichavaram, and Pichavaram Extension Area (Ramesh 2014) The region shows sub-humid climatic conditions with an average rainfall of 1310 mm and temperature of 29.8 °C ranging between 21.1° and 38.5 °C (Jayanthi 2001). The tidal amplitude is about 0.34 m at mean sea level with water depth ranging between 0.63 and 1.63 m except at Chinnavaikal where it is more in the range of 3.63–5.63 m (Ramesh 2014).

There are about 13 true mangrove species with predominance of two major species *Avicennia marina* and *Rhizophora* (Kathiresan 2000). Significantly, *A. marina* occupies 74% of the total area and is observed throughout the Pichavaram wetland (except on tide and canal banks) followed by *Rhizophora* with 15% spatial distribution (Selvam et al. 2010; Ramesh 2014). An endemic and critically endangered species *Rhizophora annamalayana* is exclusively found in this mangrove ecosystem (Kathiresan 2000). The study of Ramesh (2008) classified mangroves of Pichavaram under six zones as: Zone-I with the dominance of *A. marina* followed by *Salicornia brachiata, Suaeda maritima, Arthrocnemum indicum* and *Excoecaria agallocha*; Zone-II includes the banks of three creeks lying parallel to the seashore dominated by *Salicornia brachiata* and *A. marina*; Zone-III shows luxuriant mangroves bordered by *Rhizopora apiculata* and *Rhizopora stylosa* along with *Bruguiera cylindrica, Ceriops decandra* and *E. agallocha*; Zone-IV dominated by *Acanthus ilicifolius* which forms a community with *Avicennia officinalis, A. indicum, E. agallocha, Lumnitzera racemosa, Suaeda brachiata* and *Suaeda maritima*; Zone-V is rich in *S. maritima and Salicornia brachiata*; Zone VI exists near the Coleroon estuary. The channel on the landward side is occupied by *S. brachiata* and on the seaward side by *A. marina.* Ramesh (2014) simplified the zonation by categorizing mangroves into three zones as the *Rhizophora*

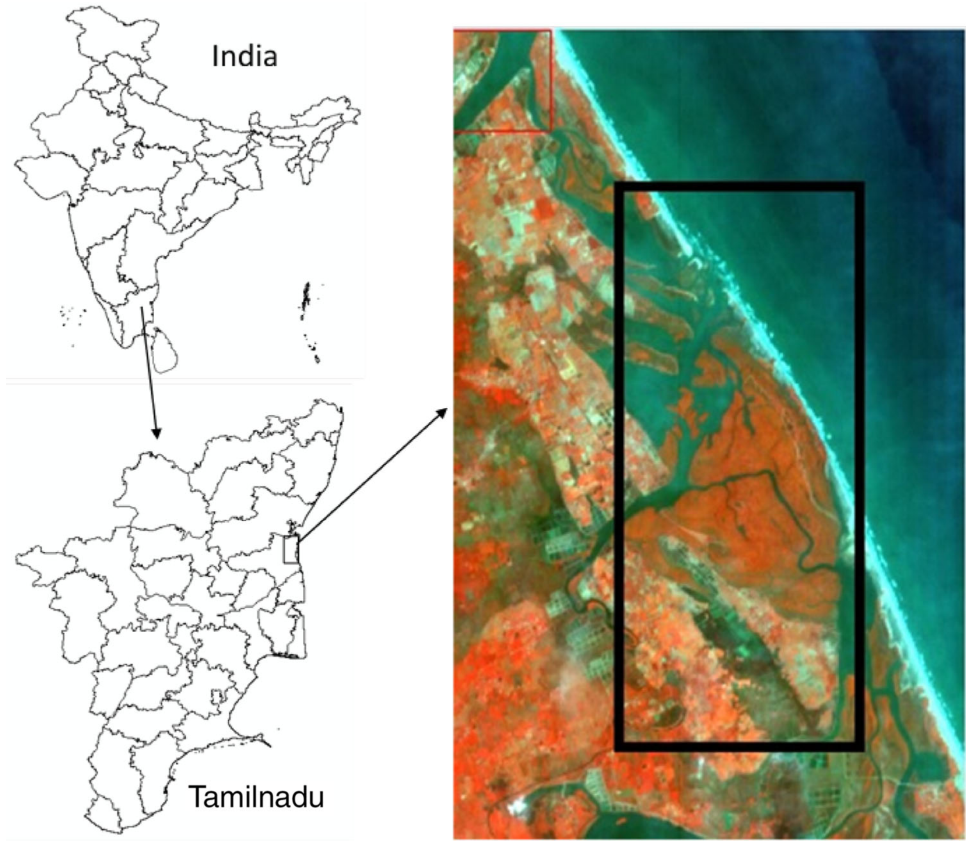

Fig. 1 Location of the study

zone, the *Avicennia* zone and the *Suaeda* zone. The area demarcated in Fig. 1 is the current study area where 11 of the 14 species (13 true and 1 associated species) as reported by Ramesh (2008) in this region have been studied viz, *A. marina, A. officinalis, Rhizophora mucronata, Rhizophora apiculata, Excoecaria agallocha, Bruguiera cylindrica, C. decandra, Aegiceras corniculatum, Acanthus ilicifolius, A. indicum, L. racemosa.* The study does not include *S. maritima, Suaeda monoica and S. brachiata* as the reference spectra for these species is not available.

Several studies have been carried out in Pichavaram wetland using optical remote sensing of moderate to high spatial resolution satellite data. The research is basically focused on, the changes in the mangrove forest, their restoration due to degraded conditions, health assessment, monitoring and LULC classification, etc. (Krishnamoorthy 1995; Selvam 2006, Jayanthi et al. 2007; Selvam et al. 2010; Gnanappazham and Selvam 2011; Kannan 2014, Kishor and Singh 2014, Chellamani et al. 2014, Sathyanathan 2014; Gandhimathi and Ramaraj 2017). Further, Ramachandran et al. (1998) initiated a study to discriminate mangrove species using spectro-radiometer and found similar radiance patterns in mangrove species with different intensity levels. As advancement, Prasad et al. (2015) developed spectral library of mangrove species using field and lab spectroscopy. Similar to the studies of Ramachandran et al. (1998), Kathiresan (2010) and Prasad et al. (2015) in the current study, we tried to map mangrove species of Pichavaram using hyperspectral satellite data and literature-derived species spectrum as ground truth information. The study is first of its kind to map mangrove species of Pichavaram ecosystems without field survey.

3 Materials and Methods

3.1 Datasets

The study used data EO-1 Hyperion data of January 3 2013 (https://earthexplorer.usgs.gov/). Hyperion is a space-borne hyperspectral sensor with 242 contiguous narrow spectral bands ranging from VNIR (Visible near-infrared) to SWIR (Short wave infrared) 400–2500 nm, with 30 m spatial resolution, and 10 nm spectral band width. Out of 242 bands, usually 198 bands are calibrated and rest are unused due to their low signal to noise ratio (Beck 2003). Hyperion covers an area of 7.5 km by 100 km per image and provides detailed spectral mapping across all 198 channels with high radiometric accuracy. Thus, there are 50 VNIR and 148 SWIR bands when the data is processed. False colour composite (FCC) of the study area was generated using band 50, 23, and 16 having a spectral wavelength 854.18, 579.45, and 505.28, respectively.

3.2 Processing

This step basically involves the removal of errors from data and final species classification using end members. A tentative methodology adopted in the current study is shown in Fig. 2.

3.3 Pre-processing

Necessary pre-processing techniques were applied: to fix bad pixels using the bad pixel list process and further recalibration of data was obtained with the gain/off values using the ASCII file; the removal of the outliers was done using the median and mean absolute deviation (MAD) as statistics for the decisions and fix out of range data (Fig. 3). The Fast Line-of-sight Atmospheric Analysis of Hypercubes (FLAASH) tool is used for correcting the atmospheric errors by selecting the input radiance image and to set the radiance scale factors. The calibrated hyperspectral radiance data are scaled into 2-byte integers. The input image is divided by the scale factors to convert the 2-byte integer data into floating point radiance values in units of $\mu W/cm^2/nm/sr$. In the current study, the gain values are 1000 as the data are radiance units ($W/m^2/\mu m/sr$) multiplied by 100.

3.4 Estimation of End Members

Hyperspectral imaging has a huge volume of data with 100 s of contiguous bands. However, it is not necessary to use all these bands for identifying and differentiating the species (Folkman 2001). Extraction of end members is required to classify the data based on spectral variation of the species visible from satellite data. Towards this, the spectral hourglass technique was used for estimating the end members. The hourglass processing flow leverages the spectrally unique species over determined nature of hyperspectral data, permitting sub-pixel target detections, material identification and unambiguous spectral un-mixing. In addition, the study also used Minimum Noise Fraction (MNF) and Pixel Purity Index (PPI) techniques. MNF transformation is used to lessen the noise in the data in addition to reducing the spectral dimensionality. Later PPI has been applied on selected MNF bands to find the most spectrally pure pixels that can be used as an input end member and is a method to reduce spatial dimension. The results obtained from the above processes helped in the *n*-dimensional visualization, including auto-clustering, and in selecting and retrieving individual end member.

3.5 Identification of Species

From the spectral hourglass process, 48 end members were extracted. As per the study of Ramesh (2008), there are 14 species found in the study area. But the reference spectra of only 11 species were found from different sources. For the species *Excoecaria agallocha, C. decandra, A. officinalis,* and *A. marina*, the spectra were referred from the work of Chakravortty (2016) and for the rest of the species, the spectra was referred from Prasad and Gnanappazhama (2014) and Manjunath and Kumar (2013). After processing the data, the pure pixel spectrum is derived using spectral hourglass process. The identification of the species is based on the absorption dips obtained from the literature and the assumption used in the study is that the dips do not change until unless the species have some deficiency or exposed to stress. The reflectance pattern is not considered as it varies with the chlorophyll content and the sun illumination angle. The 11 different species identified from the image were matched with reference material obtained through literature. Then, these spectra were used for the classification to map mangrove species of Pichavaram (Fig. 4).

3.6 Classification Techniques

Initially data was classified using unsupervised ISODATA technique (Fig. 5). This step is required to identify and estimate the areal extent of mangroves in the study area. The entire area was divided into five thematic classes as water bodies, mangroves, agricultural land, built-up and other class. Since we know the zones representing the species composition from the literature, the mean and the threshold standard deviation were also considered (Fig. 6). This helped in identifying the average spectra of the species in the study area. In the next step, data were classified using SAM. This method calculates the similarity of the two spectra by the angle between them, which is treated as the vectors in a space with dimensionally equal to its number of bands (Campbell 2009). The end members are derived from the image and are used as an input for SAM classification. The angle between the end member spectrum vector and each pixel, vector in n-D space has been compared. In simple concept, the smaller the angle, the closer and equivalent matches to the reference spectrum. Whereas, pixels that are far away than the maximum specified angle (threshold is set in radians) are unclassified. SAM classification works on the reflectance data that are pre-processed and atmospherically corrected.

Further, the study used SFF method, to compare the image spectra and the reference spectra. The SFF method is based on the least-square technique and is absorption-based

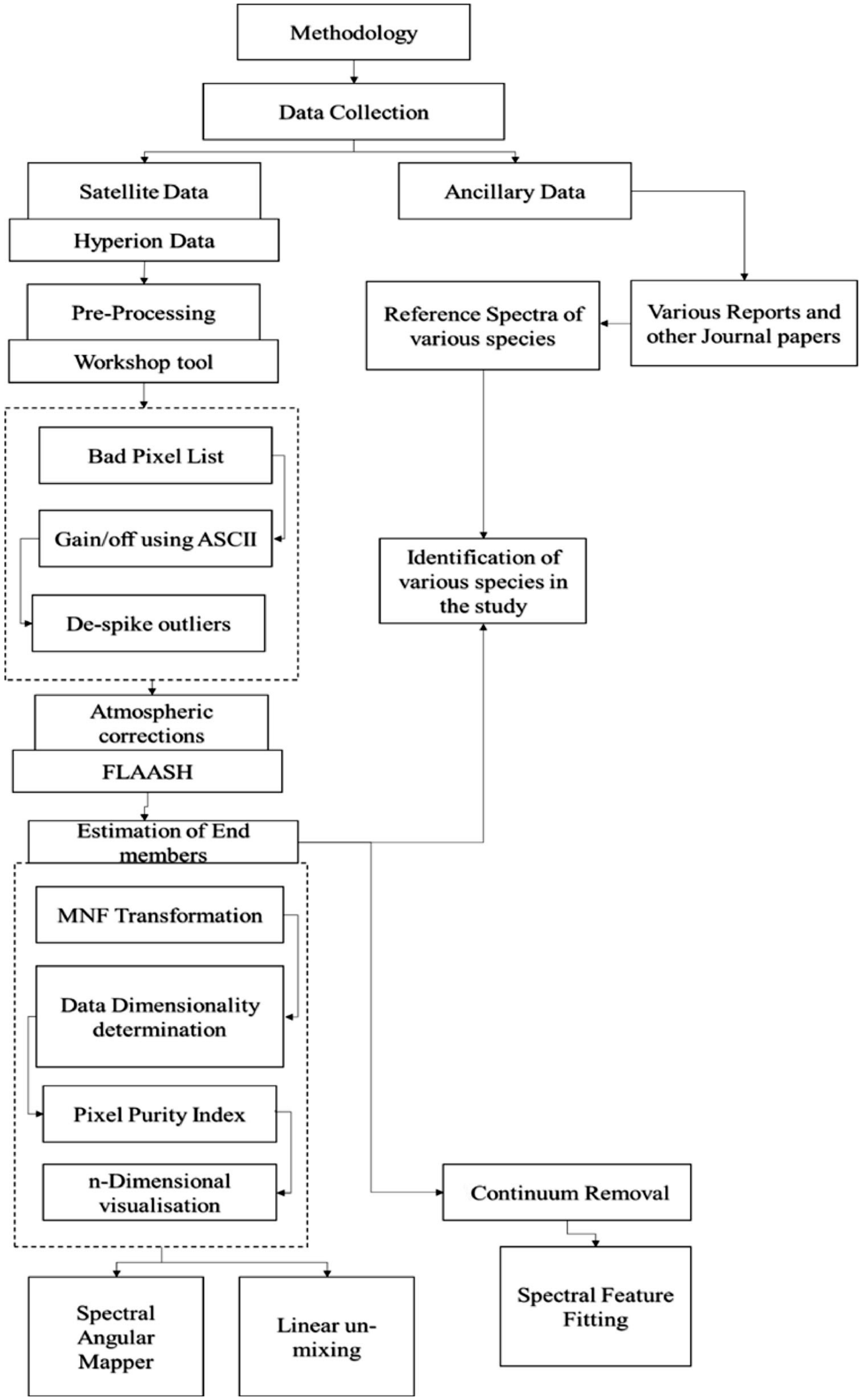

Fig. 2 Methodology of the study area

feature method. The continuum is removed from the image so that the reference spectra can be scaled to match the image spectra. The output is obtained for each single reference spectra which will be a scale and the Root Mean Square (RMS) image or a combined one. The image is related to the species abundance with respect to the

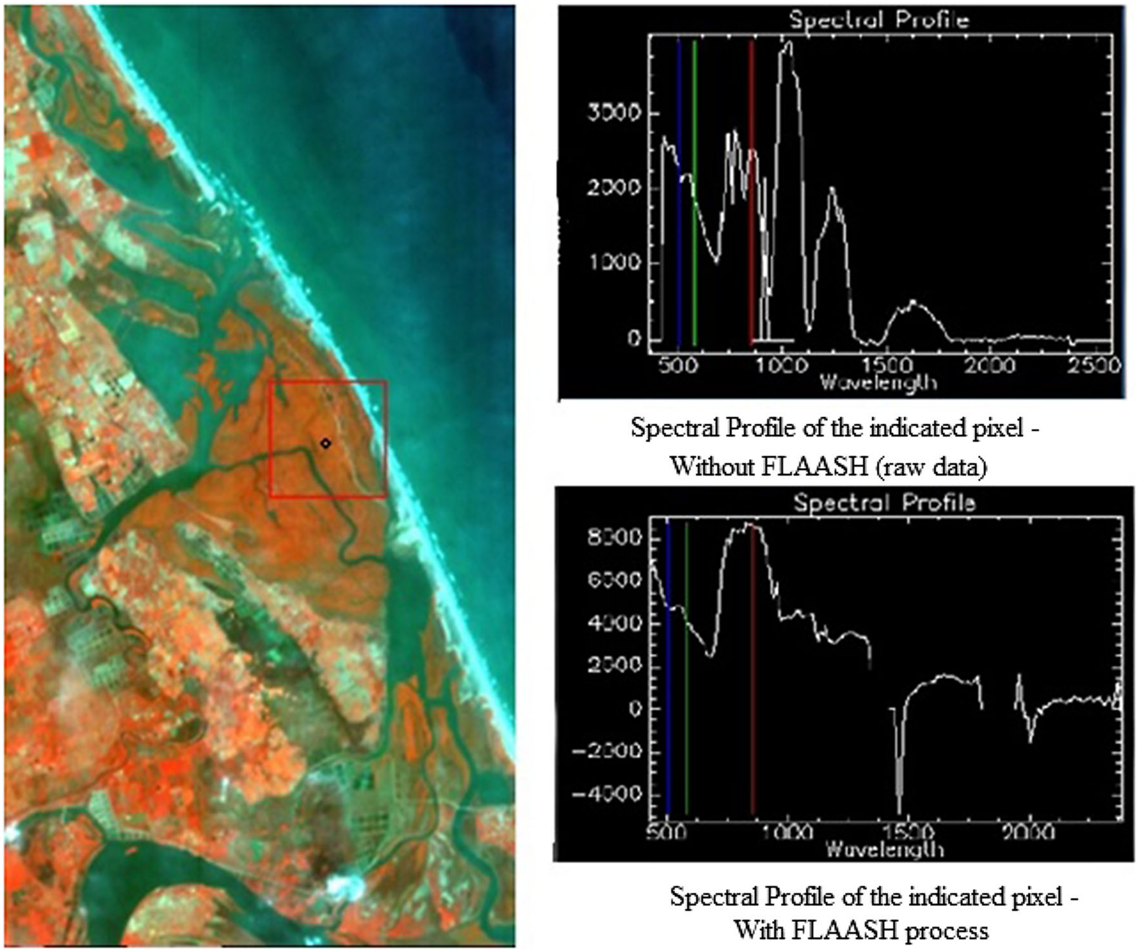

Fig. 3 Spectra of the indicated pixel before and after the FLAAH process

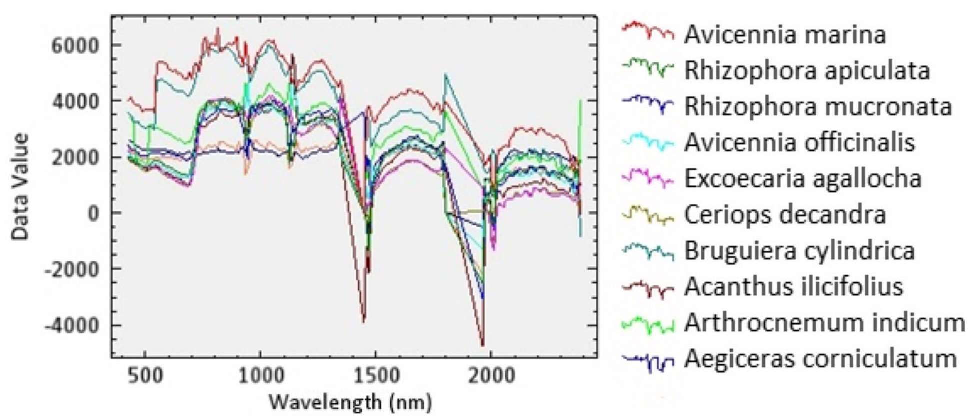

Fig. 4 End-Members Estimation and their Species

absorption feature depth. The brighter pixels in the scale and that have low RMS error refers to a better match to reference species. The dark pixels in the RMS error image indicate the low error. The RMS errors and scale image results were used to locate the areas that best match the reference spectrum. The image was also classified using SID method. This technique uses a divergence measure to match pixels to the reference spectra. The pixels will be counted as similar when the divergence is smaller. Analogous to the other classification techniques, the pixels which fall under greater threshold than the specified maximum divergence are not classified.

In all the satellite imagery, there is an issue of mixed pixels. The results of the classification can be displayed

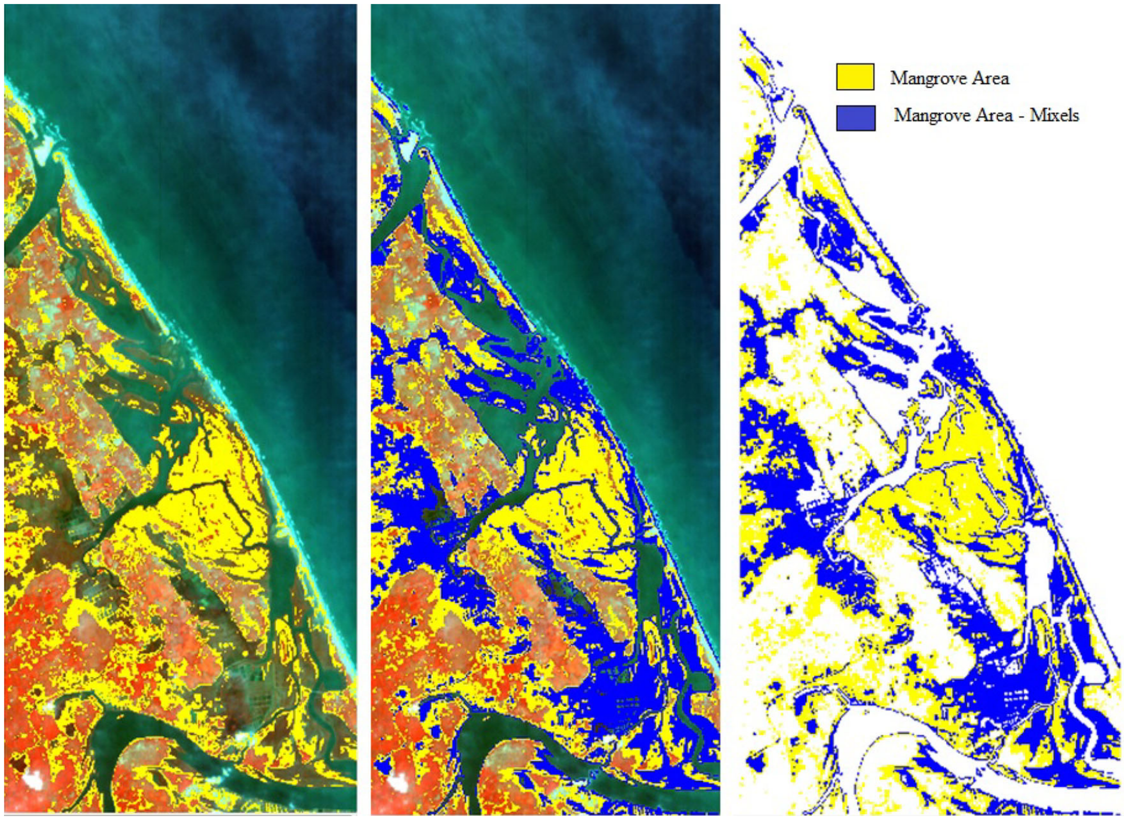

Fig. 5 ISODTA indicating the Mangrove Areas

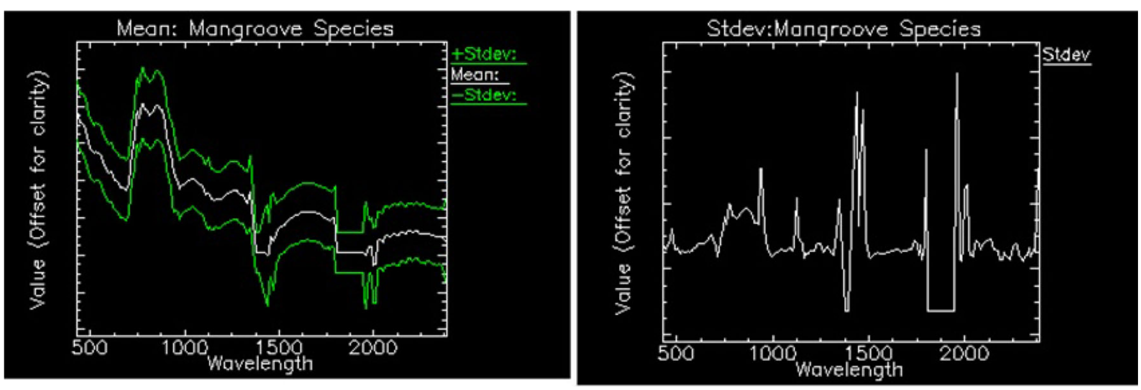

Fig. 6 The mean and the standard deviation of the Mangrove species

without considering the mixed pixels. But, the best way of classification is to perform spectral un-mixing. In this study, the Linear Spectral Un-mixing (LSU) technique has been used which rules on the basis of relative abundance of the species that are represented in the image based on the species spectral characteristics. The reflectance at each pixel of the image is assumed to be a linear combination of the reflectance of each species (or end member) present within the pixel. The RMS error image will help to determine areas of missing or incorrect end members.

3.7 Results and Discussion

The current study was able to classify the mangrove species using Hyperion data, in spite of lack of ground truth information. The reference spectrum obtained from the literature and other reports served best in generating end members (spectral signatures) for better classification and mapping of Pichavaram mangroves. However there are few pros and cons with methods applied in the current study.

The results of the SAM, SFF and SID techniques are visually analyzed and compared. It was found that SAM

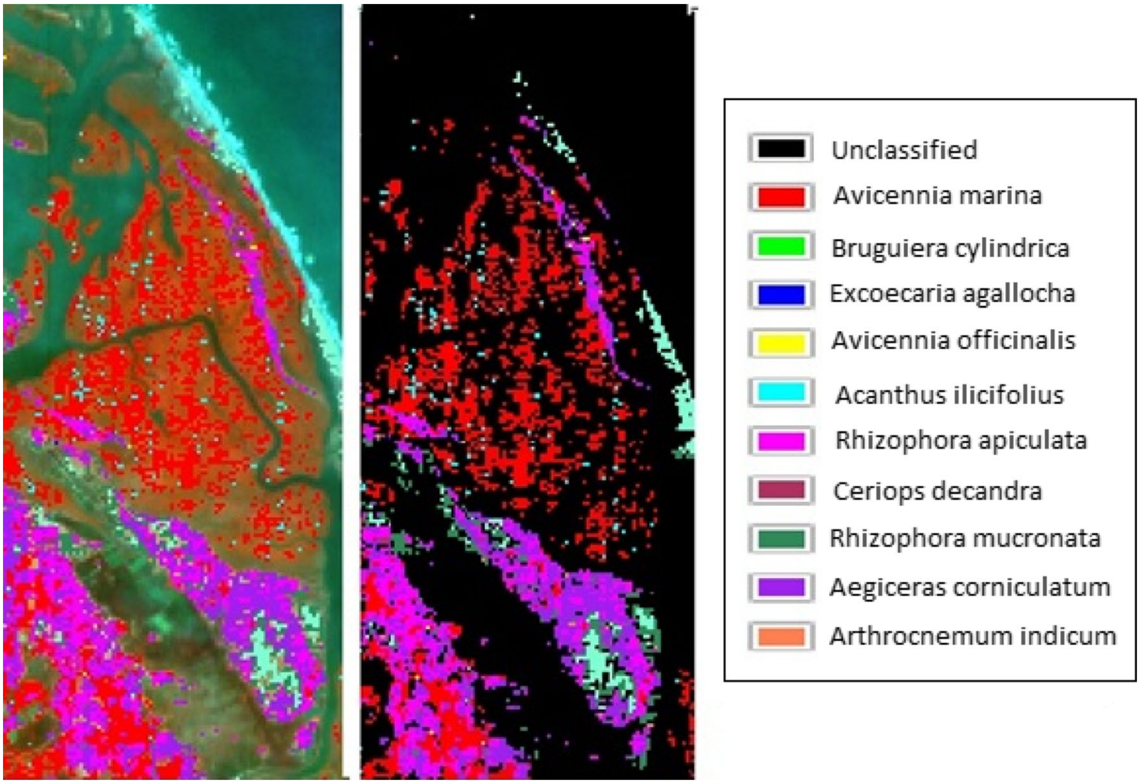

Fig. 7 Spectral angular mapping classification technique

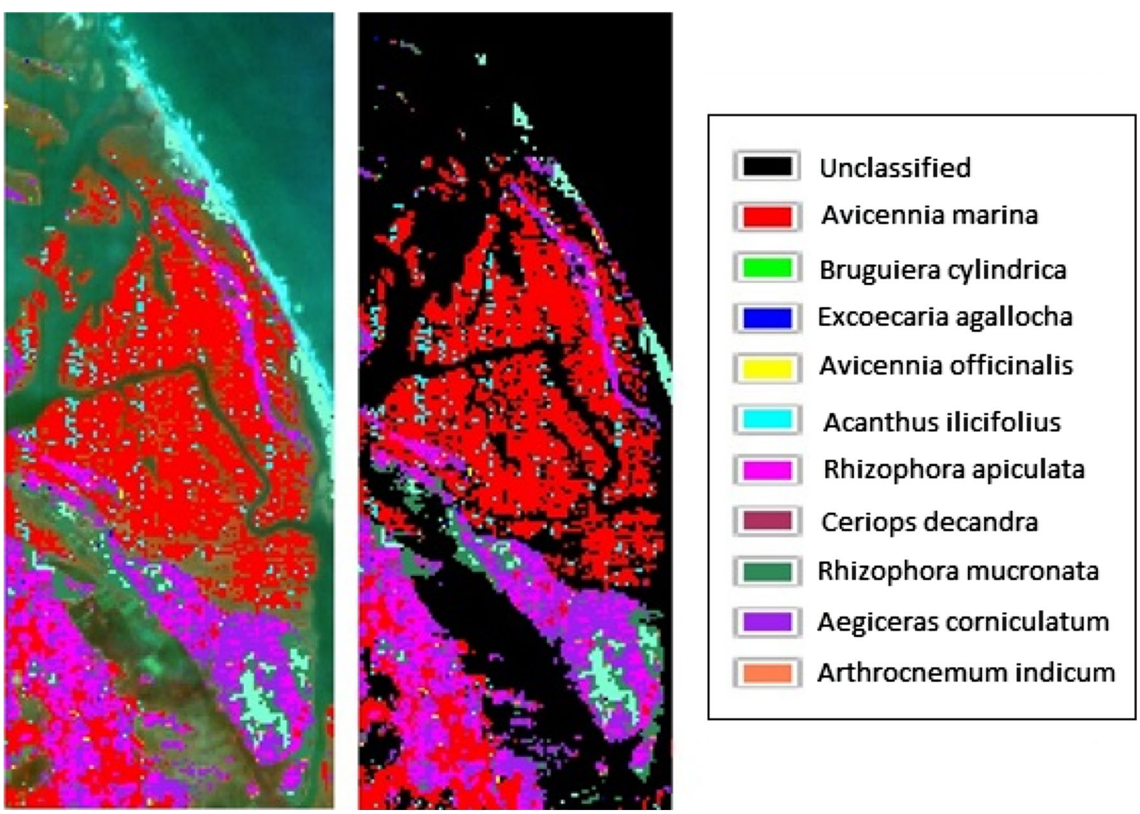

Fig. 8 Spectral feature fitting classification technique

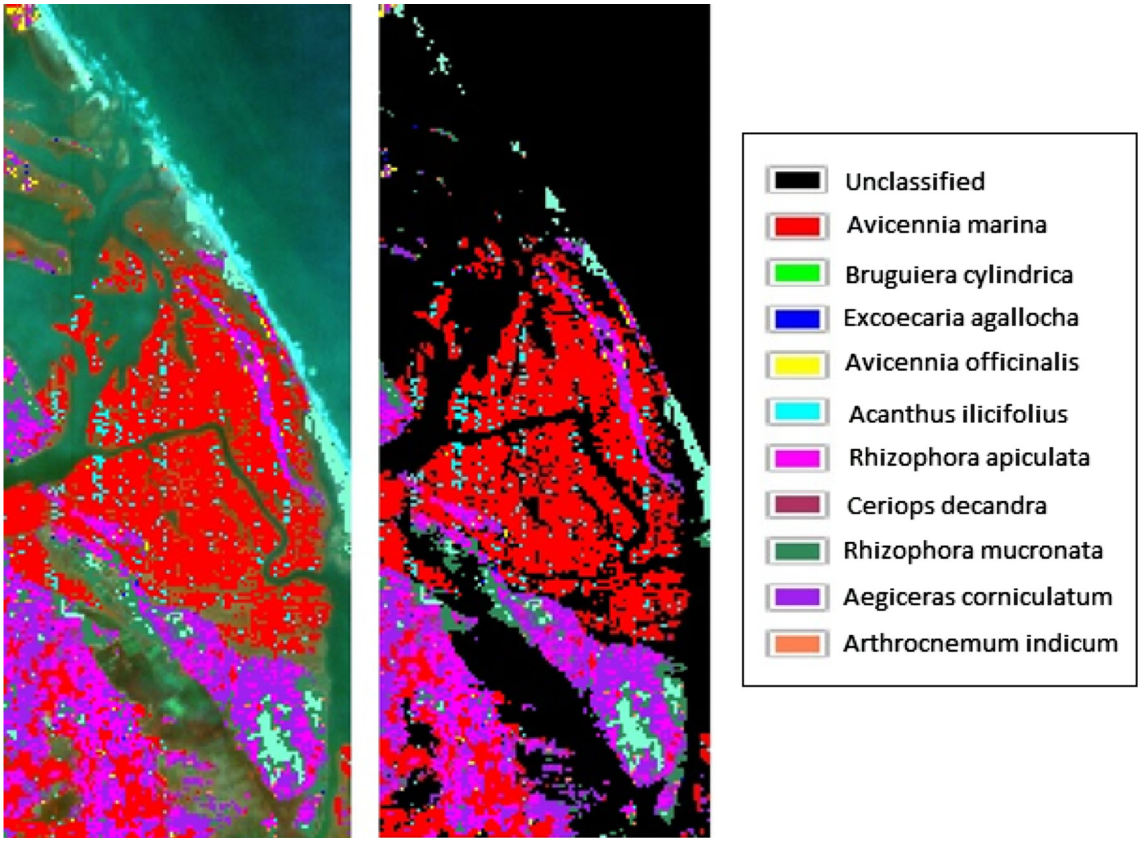

Fig. 9 Spectral information diversion

along with LSU has a better approach in delineating mangrove species. The SAM classifier rules on the vector direction to interpret the difference in the features with respect to the spectral reflectance properties, due to which the features with fewer angles are considered in the same class and rest, are unclassified. As evident from the Figs. 7, 8, and 9, the species *A. marina* and *R. apiculata* are very much, prominently seen in the study area. Strong traces of *A. officinalis*, was also observed in the south of the mangrove areas in bits and parcels (Fig. 7). This observation confirms with the results of Ramesh (2008) who also reported the occurrence of *A. officinalis* along the south zone of the Pichavaram ecosystem.

The results of the SAM classification can change with respect to the increase and decrease in angle. The problems faced during SAM have been minimized using SID. The same spectral signature is fed to the SID technique too. This helped in demarcating the other species like *Rhizopora mucronata, C. decandra,* etc. However, it is noted that in all the techniques applied there was misclassification observed inside and outside the study area boundary. Based on visual interpretation, it is noted that the misclassification is seen more in *A. marina*. This is due to more or less spectral signature matching of *Avicenna marina* with that of *Avicennia officinalis* (Fig. 8 and 9).

The other method applied was SFF, which generates the scale and the RMS image of the each single signature. The resulted ratio image with suitable threshold produced the proper dominance of the species in the study. All most all the species were classified accurately. However, with respect to *A. officinalis*, few locations were classified accurately but few areas were considered as unclassified (Fig. 8). The disadvantage of this method is that it takes much time as the entire process from the FLAASH is being carried out on the continuum removed image. Since the study had much misclassification and many pixels were unclassified due to the mixed pixels, the LSU was done. SAM is a user pre-defined classification and it can change the classification with respect to the angle; still as per the study SAM technique was the best classification technique compared to SID and SFF, as these techniques concentrate on the single or preferred species dominance (Fig. 9). So, the LSU with the combination of SAM technique helped in the extraction of the spectra and species discrimination in the current study (Figs. 10, 11).

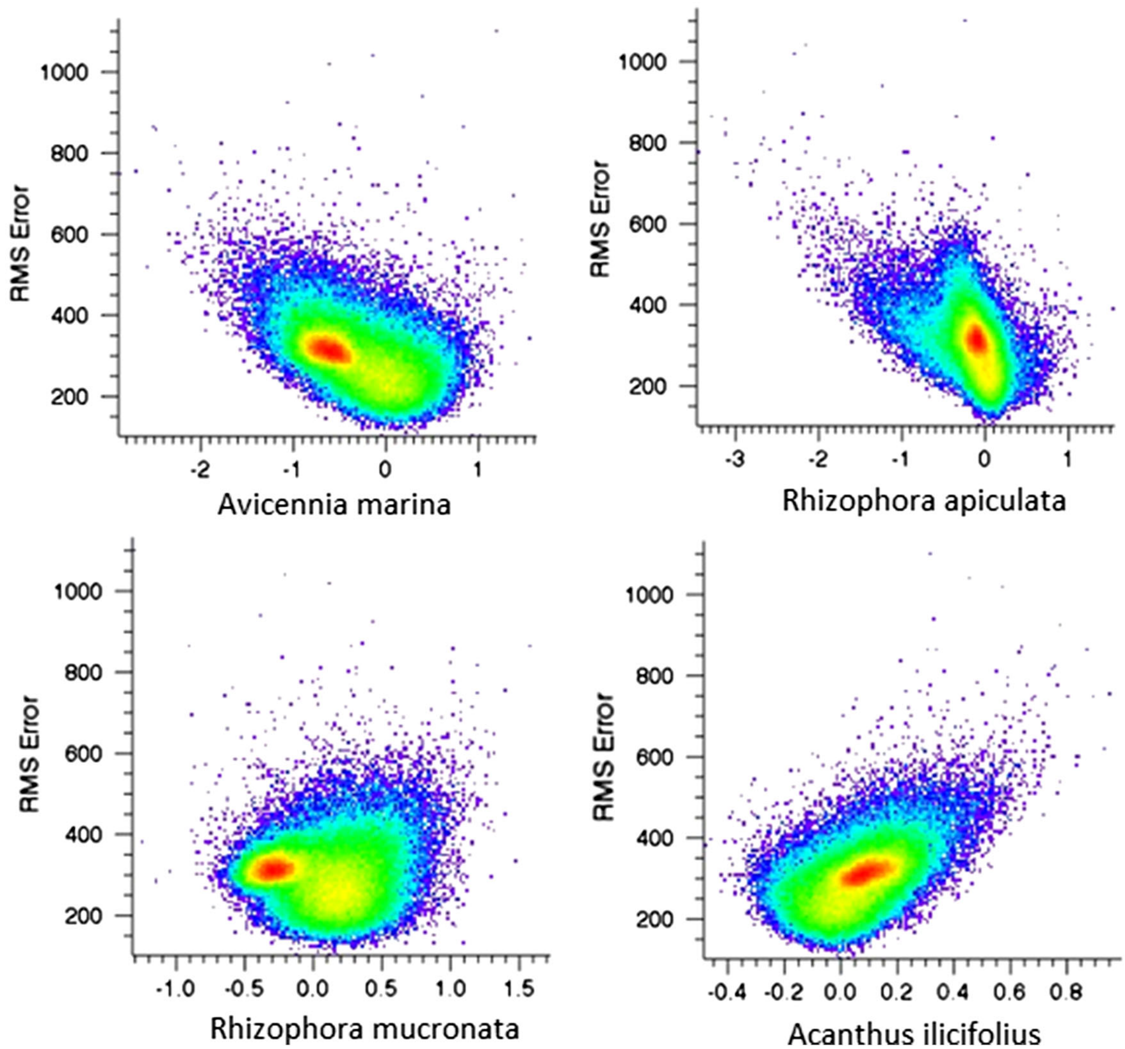

Fig. 10 Linear spectral un-mixing with respect to the species and their RMS

All the three techniques employed in the current study are feasible to replicate for species discrimination. However, the accuracy of these techniques may change depending on the type of the hyperspectral image and the terrain of the study area. In this study, it was observed that SAM technique is more accurate as almost all the species were identified and discriminated.

4 Conclusions

The current study is an attempt to map mangrove species of Pichavaram using Hyperion data without field survey. A number of hyperspectral mapping methods have been developed to extract spectral information. Three of these methods have been applied in this study, including SAM, SFF and SID. In the absence of spectrally diverse features, SAM produces unsatisfactory results. SFF processing is most extensive and the results are comparatively inaccurate. The SAM with LSU method has the most suitable and acceptable results, although some mangroves types have been mixed at few areas. This can be due to presence of mangroves in close adjacency to water and agricultural lands that produced misclassification.

The main objective of the study is to identify the species in the Pichavaram ecosystem without using the field studies and work with the reference spectrum available from the other references and reports. The purpose of the study was fulfilled to maximum extent and it is stated that such study can be carried out to any region, if any reference spectrum is being provided a priori. As per the literature, there were 14 species in Pichavaram, but since the reference spectrum from the other sources is available for only 11 species, only

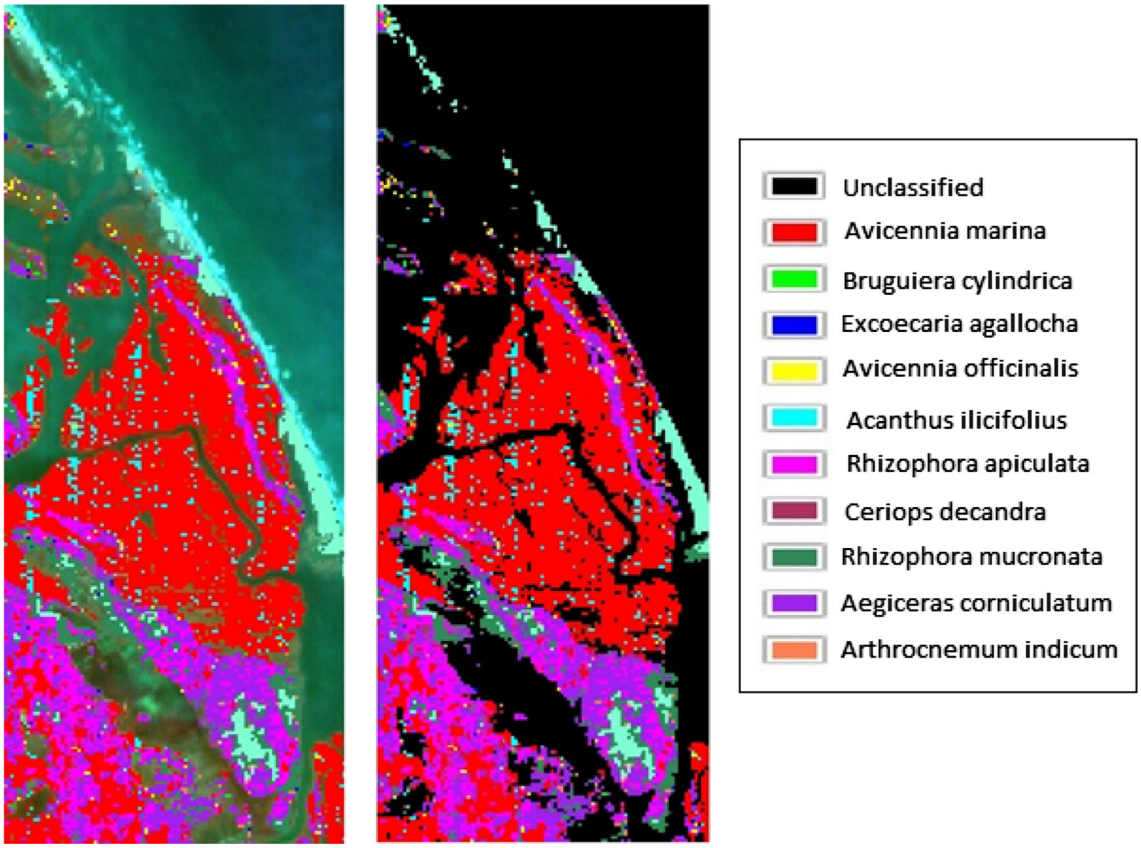

Fig. 11 The classification technique with SAM and LSM

those species were mapped. Even though 100% accuracy was not achieved, the possibility of knowing the region and its species dominance is fulfilled.

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