SPECIES DISCRIMINATION OF MANGROVES USING DERIVATIVE SPECTRAL ANALYSIS

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ABSTRACT:

Mangroves are salt tolerant trees or shrubs commonly seen in mudflats of intertidal regions of tropical and subtropical coastlines. Recent advances in field spectroscopic techniques enabled the species level discrimination among closely related vegetation types. In this study we have analysed the laboratory spectroscopy data collected from eight species of *Rhizophoraceaea* family of mangroves. The spectral data ranges between the wavelength of 350 nm and 2500 nm at a very narrow bandwidth of 1 nm. Pre-processing techniques including smoothing were done on the spectra to remove the noise before compiling it to a spectral library. Derivative analysis of the spectra was done and its corresponding first and second derivatives were obtained. Statistical analysis such as parametric and non-parametric tests were implemented on the original processed spectra as well as their respective first and second order derivatives for the identification of significant bands for species discrimination. Results have shown that red edge region (680 nm – 720 nm) and water vapour absorption region around 1150 nm and 1400 nm are optimal as they were consistent in discriminating species in reflectance spectra as well as in its first and second derivative spectra. *C. decandra* species is found to be discriminable from other species while reflectance and its derivative spectra were used. Non-parametric statistical analysis gave better results than that of parametric statistical analysis especially in SWIR 2 spectral region (1831 nm – 2500 nm).

1. INTRODUCTION

Mangroves represent vegetation ecosystem commonly thriving in silt or clay soil in the intertidal zone of tropical and subtropical coastlines (Tomlinson, 1994). In total, about 110 known plant species were identified as mangroves. Out of them, 54 species belonging to 20 genera of 16 families were categorised as true mangrove species living in the core zone (Kuenzer et al., 2011) and remaining species were represented as associated species as they found associated with mangroves and often occur in transition zone between mangrove ecosystem and terrestrial ecosystems. Mangrove community is vulnerable to extreme environmental conditions such as high temperature, high salinity, extreme tides and strong wind conditions but are well adapted and thrive in those conditions. Mangrove community forms perpetual natural resource with rich floral and faunal diversity making it as a complex ecosystem to evaluate. Mangroves form a natural barrier along the coast and act as a shield for coastal community against natural calamities such as cyclones, storm surges and tsunamis (Alongi, 2008; Kathiresan and Rajendran, 2005). *Rhizophoraceae* mangroves are found abundant along Indian coastlines which makes it as a important community to evaluate. Tomlinson (1994) categorised members of *Rhizophoraceae* family into four genera namely *Bruguiera*, *Ceriops*, *Kandelia* and *Rhizophora* with a total 18 mangrove species. In earlier days, the regular monitoring and conservation activities associated with mangroves were difficult due to the inhospitable condition prevailing there. Remote sensing technology helped the planners to make decisions regarding their monitoring, conservation and restoration activities of mangrove ecosystems in India (Ramasubramanian et al., 2006; Selvam et al., 2003). Kuenzer et al. (2011) has reviewed the studies done using remote sensing aided mangrove vegetation community mapping throughout the world. Space Application Centre (SAC) has made community level map for mangrove ecosystems in India using multispectral remote sensing data from LISS III sensor of IRS 1C and IRS 1D (Ajai et al., 2012; Nayak and Bahuguna, 2001). Over the past few decades, innovations in remote sensing technology such as hyperspectral remote sensing has made a break through by its continuous spectral data which are helpful in discriminating features having similar spectra in multispectral domain. Spectroradiometer provides pure spectral reflectance value of feature of interest placed in its field of view from its in-situ measurement. Spectral library generation for various agricultural and wetland species were successfully attempted and results indicated the existence of unique spectral signatures for particular species during its unique phase of their growth (Rao et al., 2007; Zomer et al., 2009). Spectral discrimination had been studied by utilizing field and lab reflectance data of various vegetation types such as agricultural crops (Song et al., 2011), Mediterranean species (Manevski et al., 2011) and also coastal vegetation including mangroves (Manjunath et al., 2013; Panigrahy et al., 2012; Schmidt and Skidmore, 2003; Vaiphasa et al., 2005). Apart from that both airborne and satellite based hyperspectral image data were used to discriminate mangrove species at finer levels (Held et al., 2003; Hirano et al., 2003; Koedsin and Vaiphasa, 2013; Kumar et al., 2013). Some studies were conducted based on the derivative spectral analysis of hyperspectral data such as conifer species identification using in-situ spectral data of range 350 nm to 1050 nm (Gong et al., 1997), optimal band selection for wetland species identification using second derivative spectra (Becker et al., 2005) and identifying plant stress caused

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due to gas leaks using derivative spectral ratios in red edge region (Smith et al., 2004).

In this paper we investigated the spectral discrimination among eight mangrove species of *Rhizophoraceae* family using their laboratory spectral reflectance data by implementing statistical tools such as parametric and non-parametric tests. Derivative spectral analysis was conducted to obtain their first and second derivatives for the spectral discrimination analysis and to identify the optimal wavelengths which are very consistent in spectral discrimination.

2. MATERIALS AND METHODOLOGY

2.1 Study Area

Bhitarkanika National Park is situated in north-eastern part of the state, Odisha in Indian east coast. It is located in the combined estuarine region of rivers Brahmani, Baitrani and Dhamra and has rich alluvial deposits with gently sloping topography. The total area of Bhitarkanika wildlife sanctuary is 672 sq. km., of which core area of 145 sq. km. covered by mangrove forest was declared as National park in 1998. In the year 2002, Bhitarkanika mangrove ecosystem was declared as '*Ramsar*' site – A wetland of International importance by Ramsar Convention of Wetlands. The study area lies between 20°38'19'' N - 20°47'27'' N latitudes and 86°49'26'' E - 87°05'48'' E longitudes. This area experiences semi diurnal high and low tides twice a day with the tidal amplitude ranges between 2 m – 3.5 m in upstream and 3.5 m – 6 m near to river mouths (Ravishankar et al., 2004). In Bhitarkanika, 76 mangrove species were identified. In which 30 are true species and 46 are associated species. Major species found here are *Avicennia marina, Avicennia officinalis, Ceriops decandra, Excoecaria agallocha, Heritiera fomes, Kandelia candel, Sonneratia apetala, Sonneratia caseolaris, Xylocarpus granatum* and *Xylocarpus moluccensis*.

2.2 Laboratory spectral data collection and pre-processing

Laboratory spectral data were collected from eight mangrove species of *Rhizophoracaeae* such as *Bruguiera gymnorrhiza* (BG), *Bruguiera parviflora* (BP), *Bruguiera sexangula* (BS), *Ceriops decandra* (CD), *Ceriops tagal* (CT), *Kandelia candel* (KC), *Rhizophora apiculata* (RA) and *Rhizophora mucronata* (RM) which are prominent in Bhitarkanika National Park were chosen for this analysis. Spectral data were collected from twenty piles of freshly picked leaves of each of the eight species using Analytical Spectral Device (ASD) Fieldspec® 3 spectroradiometer in a dark room environment. The sampling interval in which Fieldspec® 3 records reflectance are 1.4 nm in the wavelength range between 350 nm and 1000 nm and of 3 nm in the wavelength range between 1001 nm and 2500 nm. About 150 spectra were recorded for each species. Quartz-tungsten filament halogen lamp which gives consistent illumination in the range of 400 nm to 2500 nm was selected as the artificial source of light.

The collected spectra were subjected to pre-processing techniques such as a) splice correction at 1000 nm and 1830 nm, b) removal of non-illuminated bands between 350 nm and 400 nm and c) smoothing using Savitzky- Golay filter (polynomial order 2 and filter size 15). Then the processed spectra were compiled and spectral library was generated (Figure 1).

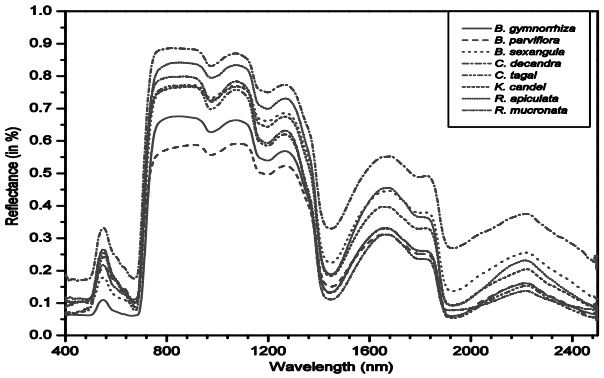

Figure 1. Laboratory spectra of *Rhizophoraceae* mangroves

2.3 Derivative spectral analysis

Spectral derivative analysis was done by dividing the difference between successive spectral values by its wavelength interval (bandwidth). Finite approximation method could be used to estimate derivatives based on the spectral resolution of the data (i.e., bandwidth) Δλ (Tsai and Philpot, 1998). The formula used to estimate the first derivative is

$$\left.\frac{ds}{d\lambda}\right|_i \approx \frac{s(\lambda_i)-s(\lambda_j)}{\Delta\lambda},$$

where, $\Delta\lambda$ is the band width which is given as $\Delta\lambda = \lambda_j - \lambda_i$ and also $\lambda_j > \lambda_i$. Here $\Delta\lambda$ (1nm) is constant throughout the spectrum.

The second derivative was calculated from the first derivative and it could be expressed as

$$\left.\frac{d^2y}{dx^2}\right|_j = \frac{d}{d\lambda}\left(\frac{ds}{d\lambda}\right)\Big|_j \approx \frac{s(\lambda_i)-2s(\lambda_j)+s(\lambda_k)}{(\Delta\lambda)^2}$$

where, $\Delta\lambda = \lambda_k - \lambda_j = \lambda_j - \lambda_i$ and $\lambda_k > \lambda_j > \lambda_i$.

The spectral library was compiled from first and second order derivatives obtained from spectra of eight species. An example of these three spectra of *R. apiculata* is given in Figure 2.

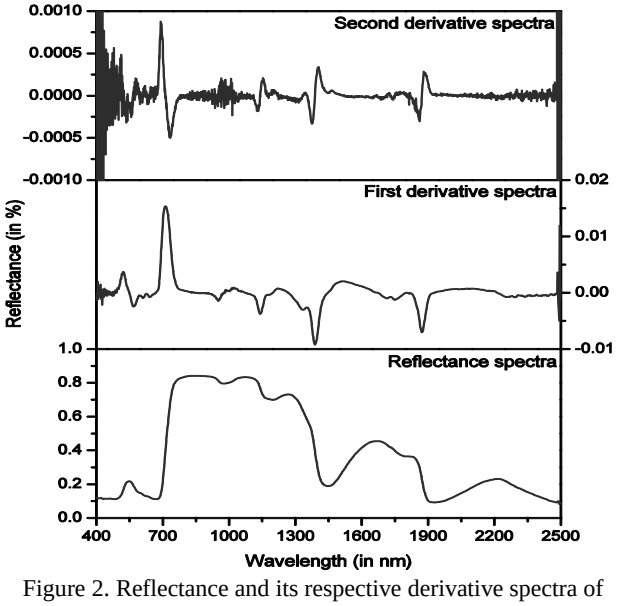

Figure 2. Reflectance and its respective derivative spectra of mangrove species *Rhizophora apiculata*

2.4 Statistical analysis for the identification of spectrally discriminable bands

In the present study we used both parametric and non-parametric statistical analysis to identify bands having separability. For parametric statistical analysis, One way Analysis of Variance (ANOVA) test was chosen by assuming the null hypothesis

$H_o : \mu_1 = \mu_2 = \ldots\ldots = \mu_8$

against the alternative hypothesis,

$H_a : \mu_1 \neq \mu_2 \neq \ldots\ldots \neq \mu_8$.

Here μ represents the mean spectral reflectance. This test was performed along with pair-wise Bonfferoni post-hoc test (McHugh, 2011) at each wavelength for 95% and 99% confidence level. The homogeneity of variance was tested prior to the analysis as it is a prerequisite to perform one way ANOVA test.

For non-parametric statistical analysis, Kruskal Wallis test was selected by assuming the null hypothesis

$H_o: \eta_1 = \eta_2 = \ldots\ldots\ldots = \eta_8$

against the alternative hypothesis,

$H_a: \eta_1 \neq \eta_2 \neq \ldots\ldots\ldots \neq \eta_8$

at every wavelength location considered for 95% and 99% confidence interval. Here η represents the median spectral reflectance. Kruskal-Wallis test is similar to One-way ANOVA test that can be performed on ordinal (ranked) data. Mann-Whitney U test compares median spectral reflectance of two species to find out the spectral difference between them (Sheskin, 2004) at each wavelength location. Parametric and non-parametric tests were implemented on total of 28 such possible pairs of species combinations.

3. RESULTS AND DISCUSSION

The wavelengths (bands) which are spectrally significant for each species pairs were identified using parametric and non-parametric test at 95% and 99% confidence level. The results of both tests at 99% confidence interval for reflectance spectra and its corresponding first and second derivative spectra (here after referred as "three cases") are given in Table 1.

3.1 Identification of spectrally significant bands using parametric statistical analysis:

The wavelength location of spectrally significant bands obtained from parametric one-way ANOVA paired with Bonfferoni post-hoc test for 28 species pairs in three cases were identified. Scatter plot representing the location of significant wavelengths and the frequency plot representing number of the spectrally significant pairs at each wavelength in three cases are given in Figure 3.

In reflectance spectra, there are 8 species pairs which are separable in every wavelength and they are BG vs BS, BG vs CD, BP vs CD, BS vs CD, CD vs CT, CD vs KC, CD vs RA and CD vs RM. Thus in reflectance mode the species *C. decandra* was found to be consistently separable from all the other species. Apart from that other species pairs which are separable in more than 2000 bands are BG vs KC, BG vs RA, BP vs BS, BP vs RA, BS vs CT, CT vs KC and RA vs RM. The species pair with least separability was identified as BG vs BP which was separable only in 903 bands. In first derivative spectra, species pairs such as BP vs RM, BS vs RM and RA vs RM were identified as most separable species pairs with more than 1200 significant bands each. *R.mucronata* is found to be the spectrally significant species while first derivative spectra were used. BG vs CT, BG vs KC and BS vs KC were identified as least separable species pairs. While second derivative spectra was used, BP vs CD, BS vs CD and CD vs RA were found to be more separable species pairs with almost more than 400 significant bands each. *C. decandra* was spectrally significant when second derivative spectra were used. Least separable species pairs were BG vs CT, CT vs KC and CT vs RM making *C. tagal*, the least separable species while second derivative spectra were used.

Table 1. Number of significant wavelengths derived from parametric and non-parametric statistical analysis for each species pair at 99% confidence level while reflectance and its corresponding derivative spectra were used. The results of parametric one way ANOVA is given in lower left half and non-parametric Mann-Whitney U test (shaded in gray colour) is given in upper right half of the table

REFLECTANCE SPECTRA								
	BG	**BP**	**BS**	**CD**	**CT**	**KC**	**RA**	**RM**
BG		1191	2100	2100	2045	2021	2095	1648
BP	903		2089	2100	1938	1960	2074	1807
BS	2100	2058		2100	2084	1415	1937	1704
CD	2100	2100	2100		2100	2100	2100	2100
CT	1383	1262	2048	2100		2050	2081	1771
KC	2015	1987	1360	2100	2038		1477	1423
RA	2056	2028	1695	2100	1994	1509		2040
RM	1782	1471	1724	2100	1164	1562	2003	
FIRST DERIVATIVE SPECTRA								
	BG	**BP**	**BS**	**CD**	**CT**	**KC**	**RA**	**RM**
BG		1297	1016	1196	1305	1143	805	1004
BP	1029		1020	1104	961	1335	1111	1179
BS	906	925		1194	1151	1311	1242	1328
CD	999	1172	825		1327	732	1051	1091
CT	707	1040	1050	1053		1160	863	1132
KC	731	942	697	871	816		1077	1199
RA	893	1191	1107	1146	1123	967		1495
RM	1074	1210	1256	1089	812	1013	1371	
SECOND DERIVATIVE SPECTRA								
	BG	**BP**	**BS**	**CD**	**CT**	**KC**	**RA**	**RM**
BG		414	339	433	410	386	294	342
BP	170		400	418	354	418	275	352
BS	202	278		383	413	414	368	428
CD	342	395	414		420	292	353	325
CT	111	167	241	299		362	271	313
KC	165	194	233	263	123		357	339
RA	167	260	269	407	183	190		379
RM	220	247	330	384	122	176	293	

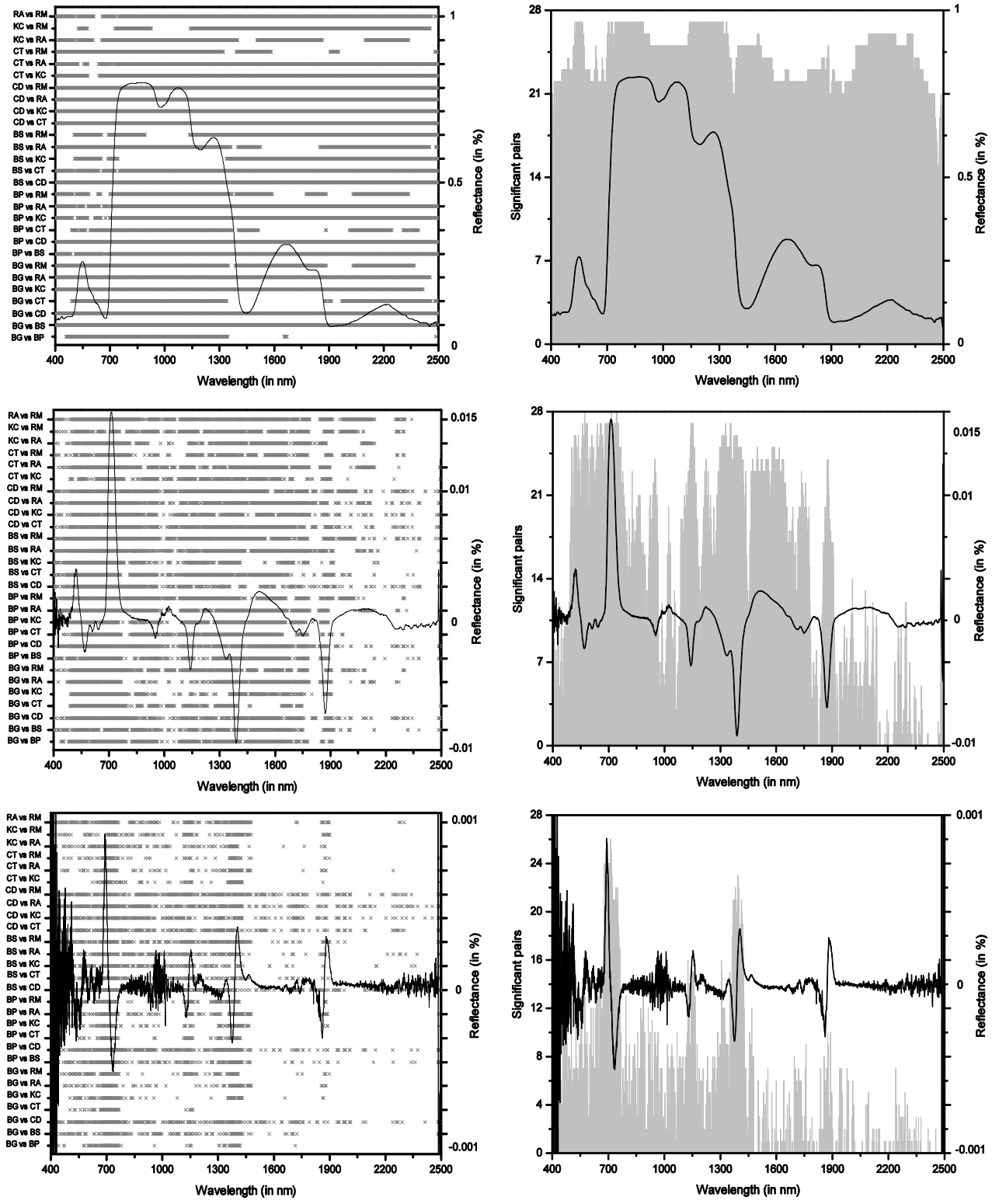

Figure 3. (i) Scatter plots (left side) and (ii) frequency plots (right side) depicting the location of spectrally significant (separable) bands and the number of statistically significant pairs at each wavelength location respectively obtained from parametric One way ANOVA paired with Bonfferoni test for 28 species pairs in three cases (Row wise - top to bottom: Reflectance spectra, First Derivative spectra and Second Derivative spectra) at 99% confidence interval. The average spectrum of *R. apiculata* species in each case is plotted in their respective scatter and frequency plots for easy interpretation.

This contribution has been peer-reviewed. The double-blind peer-review was conducted on the basis of the full paper.
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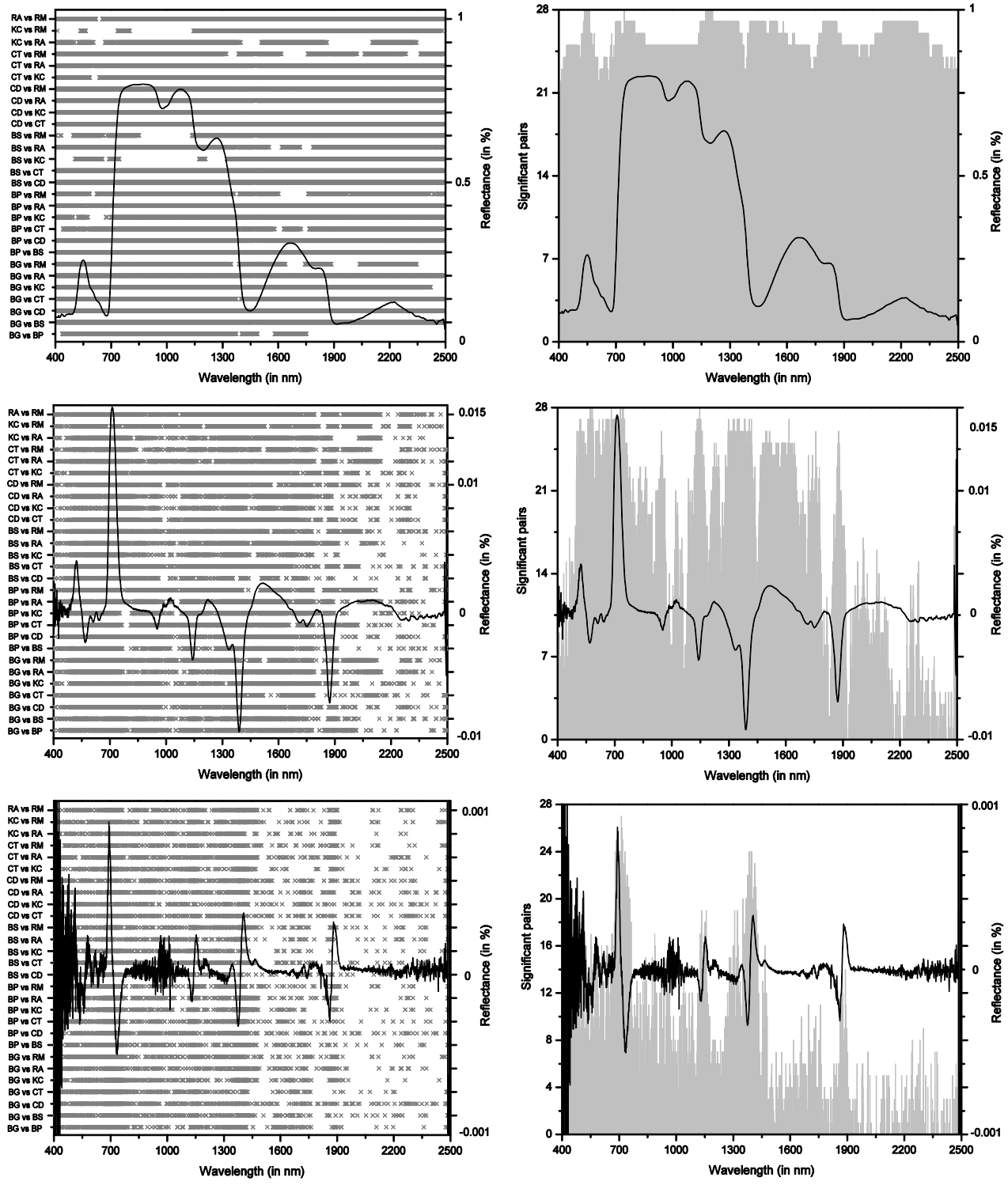

Figure 4. (i) Scatter plots (left side) and (ii) frequency plots (right side) depicting the location of spectrally significant (separable) bands and the number of statistically significant pairs at each wavelength location respectively obtained from non-parametric Kruskal Wallis test along with Mann Whitney U test for 28 species pairs in three cases (Row wise - top to bottom: Reflectance spectra, First Derivative spectra and Second Derivative spectra) at 99% confidence interval. The average spectrum of *R. apiculata* species in each case is plotted in their respective scatter and frequency plots for easy interpretation.

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Regarding the location of spectrally significant bands (wavelengths) in the spectral domain of 401 nm – 2500 nm, most of the species pairs are separable in green reflectance and red edge region. In first derivative spectra case, separability has become low in regions such as blue (400-500nm), absorption band around 1050 nm, minor absorption band around 1800 nm and SWIR region between 1950 nm and 2500 nm. In first derivative spectra, most of the species are separable in VNIR and SWIR 1 wavelength regions but not in SWIR 2 region. While considering the second derivative spectra case, higher separability was observed in red edge region (680 nm – 750 nm) and also in water vapour absorption region around 1390 nm. Considering the species pairs, most of the species pairs are separable in region between 400 nm and 1350 nm except BG vs BP, BG vs CT, BG vs KC, BG vs RA, BG vs RM, BP vs CT, BP vs KC, BP vs RA, CT vs KC, CT vs RA, CT vs RM and KC vs RM. The species *C. decandra* alone is separable from other species in most of the wavelengths in the region between 1451 nm and 2500 nm.

3.2 Identification of spectrally significant bands using non-parametric statistical analysis:

The wavelength location of spectrally significant bands obtained from non-parametric Kruskal Wallis test along with Mann Whitney U-test for 28 species pairs using reflectance and corresponding first and second order derivative spectra were identified. The scatter plot representing the wavelength location of spectrally significant bands for 28 species pairs and frequency plot showing the number of spectrally discriminable pairs at each wavelength are given in Figure 4. The results reveal that spectral separability among species of *Rhizophoraceae* is found to be in higher order while analysed using non-parametric tests than parametric tests considered for this study. In reflectance spectra, eight species pairs which were completely discriminable at all wavelengths in parametric test were also completely discriminable while non-parametric test was applied. Apart from these eight species pairs species pairs such as BS vs BP, BS vs CT, BG vs RA, BP vs RA and CT vs RA were discriminable in most of the bands (>2074 bands). *C. decandra* and *R. apiculata* were identified as most discriminable species while reflectance spectra were used. Species pair with minimum separability was BP vs BG which was also similar to that of parametric test results. In first derivative spectra, most separability was obtained for CD vs CT, KC vs BP, KC vs BS, BS vs RM, RA vs RM. *B. sexangula* was found to be consistently separable from other species in first derivative spectra case. Minimum separability was observed in pairs such as BG vs RA, CD vs KC and CT vs RA. While in second derivative spectra, maximum separability was observed in species pairs such as BG vs CD, BP vs CD, BP vs KC and BS vs RM while minimum separability was observed in KC vs CD, BP vs RA and CT vs RA.

While focusing on the distribution of spectrally significant bands of 28 species pairs in the wavelength domain considered, it is almost similar to parametric statistical test in reflectance spectra case with some exceptions like BG vs CT and BP vs CT. But in first derivative spectra the distribution of spectrally separable bands has improved in SWIR 2 region beyond 1900 nm in most cases when compared with parametric statistical test results. Also, separability in wavelengths regions around 450 nm and 1000 nm has improved in some cases such as BG vs CT, BG vs KC, BG vs RA, CT vs KC, CT vs RM and KC vs RA. In second derivative spectra case, there was much improvement observed in the spectrally separable bands between 1450 nm and 1950 nm. Wavelengths beyond 1950 nm had also shown slight improvement in spectral separability in most cases.

When comparing the frequency plots of three cases in figure 3 and figure 4, it is evident that frequency has certainly improved in non-parametric analysis when compared to that of parametric analysis. In reflectance spectra case, the frequency has increased in green reflectance (~550 nm), Red edge (680 nm – 720 nm), water absorption at 1150 nm, SWIR bands (1450 nm - 2000 nm) and in SWIR 2 region (beyond 2350 nm). In first derivative spectra case, much improvement was evident in region around 1000 nm and bands beyond 1900 nm. While in second derivative spectra, considerable improvement of frequency was observed beyond 1460 nm.

While summarising the results, it is evident that there is significant difference between mangrove species of *Rhizophoraceae* in the spectral domain considered for this study. *C. decandra* has higher spectral separability from other species in reflectance and second derivative spectra cases. Red edge region (680 nm – 720 nm) and water vapour absorption band around 1150 nm and 1400 nm are consistent in discriminating species in reflectance spectra as well its first and second derivative spectra. Non-parametric statistical analysis gave better results than parametric statistical analysis especially in SWIR 2 spectral region (1831 nm – 2500 nm) of second derivative spectra. Results imply the dissimilarity in internal cell arrangement and thickness of leaves prevailing in different species of *Rhizophoraceae*.

4. CONCLUSION

In this paper, it is studied that how parametric and non-parametric statistical analysis could be used for discriminating species those belong to same family using laboratory spectral signatures. Separability using derivative spectral analysis was experimented and the results were useful to identify that red edge region and water vapour absorption region around 1450 nm were consistent in discriminating *Rhizophoracea* species. The spectral reflectance of leaves is characteristic of biochemical variables (i.e., cell pigments) such as chlorophyll, carotenoids etc. which is noticed in wavelength interval of 350 nm – 700 nm (Das et al., 2002). The spectral variability in near infra-red and shortwave IR region indicates the difference in amount of scattering due to multiple refractions and reflections at the boundary between cellular walls and mesophyll cells among species, presence of nitrogen, protein, lignin and absorption due to water content present in leaves (Panigrahy et al., 2012; Tomlinson, 1994). The difference in thickness of 'achlorophyllous' tissues among *Rhizophoraceae* species also has a major impact on the difference in spectral reflectance in NIR and SWIR regions.

This method has successfully established the discrimination of mangrove species of Rhizophoraceae family which was reported "poorly discriminable" in earlier studies. Though overall separability among species was decreased when derivative spectra was used, the results were useful to identify most consistent bands for discriminating *Rhizophoraceae* species. The methodology followed would be used in discriminating the species for the selection of optimal bands while using hyperspectral satellite data to enhance the classification accuracy.

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