CHAPTER 4

Discussion

4.1 Structural and floristic dynamics of the study area

Structural and floristic dynamics (expressed as Holdridge Complexity Index HCI ,Basal area BA, Shannon diversity index H' and density of a species) for mixed vegetation covers of SWS showed similarity with other studies performed on tropical mixed deciduous forests world wide. Range of structural and floristic components measured in present study are comparable to that of Singh et al. (2005), who measured structural components (HCI, BA and H') for moist deciduous forest of Madhya Pradesh, India. Kalacska et al. (2005) measured related structural components (HCI, BA and H') for tropical dry forest of Santa rosa national park in north-western Costa Rica. Range of structural components in present study is also comparable to this study. Measured structural and floristic parameters in present study are comparable with the standardized range reported by Murphy and Lugo (1986) from world wide tropical dry forests sites. Earlier, Sagar et al. (2003) and Gairola et al. (2011) reported Shannon diversity index and species density across different dry tropical forests sites of India. Similar range of Shannon diversity index and species density was observed in present study. Madugundu et al. (2008) measured basal area of deciduous forests of Karnataka, India (basal area 26-42 m^2 ha^{-1}). Range of basal area in present study (basal area 16.94-44.49 m^2 ha^{-1}) was comparable to this study. Basal area range obtained in this study is also analogous to range provided by kumar et al. (2006) for different forest communities in the tropics.

This study area supports a mosaic of vegetation covers successional stages. The structure of the regenerating vegetation has been greatly affected by altering of Land Use Land cover (LULC) and plantation activities of Gujarat forest department. Variation in the range of Normalized Difference Vegetative Index (NDVI) values in three different succession classes of vegetation in SWS was observed. Spectra coming from this area also differed. By utilizing remote sensing data change detection in forest covers because of human intervention can be easily recorded and monitored across large spatial scale. Studies in this respect could involve the detection and characterization of plant successional groups, which would be of crucial importance for conservation purposes (Sanchez-Azofeifa, 2005). Examination of average reflectance spectra (October) for the different vegetation types indicated that the Hyperion data provided many possibilities for separating vegetation successional groups using specific narrow bands throughout the 400 to 2350 nm spectral range. Earlier, Huete et al. (2008) reported that most of the spectral variations among tropical rainforest, regenerating successional forest, and pasture/agriculture occur in the NIR region, but there is also high spectral variability in the shortwave infrared (SWIR) region. Results of this study conforms this report.

Linear regression models between basal area and two indices (HCI and H') worked well. These linear regression models can be useful to get estimations of species complexity and diversity of tropical deciduous forests using basal area measurements. These models can be tested for forest covers with similar pattern of vegetation.

4.2 Phenological changes and Hyperion reflectance spectra

Reflectance spectra acquired from two distinct phenological stages of vegetation showed marked difference in pattern and shape. Green foliage, canopy area and density of trees influenced spectra coming from each vegetation cover. Spectra coming from October month reflected the lush green state of vegetation and the ones coming from April month showed deciduous nature of vegetation cover. Appreciable differences between April and October reflectance spectra revealed contrasting phenological stages of vegetation. Results showed potential of Hyperion reflectance spectra in deciphering vegetation phenology. Earlier, Huete et al., (2008) reported similar phenological changes using Hyperion reflectance spectra of tropical forests. Results of this study are in confirmity. Average reflectance spectra acquired from images of April and October showed major variation in reflectance pattern in visible (400-800 nm) region. Changes in the blue and red region of electromagnetic spectrum are largely taking place due to the amount of chlorophyll (Asner, 2008). As the leaf senesces, lower concentrations of chlorophyll greatly reduce the amount of absorption throughout the visible region, thereby increasing reflectance (Clark et al., 2005). Distinct difference seen at visible-NIR region of the spectra coming from October and April indicate the influence of pigmentation on reflectance spectra as reported earlier (Sims and Gamon, 2002). Dash et al. (2010) estimated phenological variables of vegetation covers of India using space borne Medium Resolution Imaging Spectrometer (MERIS) data. Their study showed the importance of variations in terrestrial chlorophyll content in the prediction of phenology of the vegetation. Similar inferences can be drawn from the results reported here. In present study lush vegetation and difference in canopy structure in post monsoon season (October) of SWS resulted in variation in reflectance within NIR region (700-1300 nm). Martin et al., 2008 said that NIR plateau is also strongly influenced by water and canopy structure. Results obtained in present study are analogous to this study. Earlier, Serrano et al., 2000 reported that NIR regions have been found to have liquid water absorption features. Change seen in the reflectance in NIR region can be attributed to the change in water content in foliage. Water content of the foliage also influenced the pattern of NIR spectra reflecting phenological status of vegetation cover. Similar inference was made earlier by Ceccato et al. (2001).

4.3 Hyperion reflectance spectra (October) for different vegetation covers of SWS

Reflectance spectra for the different vegetation covers (teak, bamboo and mixed vegetation) of SWS showed typical patterns of vegetation reflectance: low VIS reflectance caused by absorption by chlorophyll and other pigments, high NIR reflectance due to multiple-scattering within the leaf structure, weak NIR water absorption features at NIR region, and moderate reflectance in SWIR region (Gausman, 1985; Roberts et al., 2004). In present study differences in the spectral reflectance of high and low density quadrats are variable between wavelength regions but are greatest within the NIR and SWIR regions. Reflectance spectra showed that high density quadrats of teak and bamboo vegetation covers of October month demonstrated high reflectance in NIR and SWIR region. Within the NIR region, reflectance is largely a function of the type, density, and arrangement of leaves as these influence photon scattering (Clark et al., 2005). In the present study greater stem density holding thick foliage resulted in high photon scattering in high density quadrats of teak and bamboo which gave rise to high reflectance in NIR region. In present study large variation observed in reflectance at near infrared (NIR) and short wave infrared (SWIR) regions can also be explained by large differences in Leaf Area Index (LAI) values in low density and high density quadrats. Thenkabail et al. (2004) suggested that there is strong relationship between LAI and reflectance in NIR and SWIR regions. Many studies have reported that reflectance in NIR and SWIR region is affected by change in LAI values (Brown et al., 2000; Cohen and Goward, 2004; Lee et al., 2004; Nemani et al., 1993; Schlerf et al., 2005; Darvishzadeh et al., 2008). Larger differences in the LAI values of teak and bamboo quadrats have shown their influence in reflectance values of NIR and SWIR regions.

4.4 Species level classification of Hyperion data

4.4.1 Dimentionality reduction using Stepwise Discriminant Analysis (SDA)

High data dimensionality is the key problem with hyperspectral image processing. Therefore, powerful statistical methods are required to reduce dimensionality (Chan and Palinckx, 2008). Dimensionality reduction is mostly done by band selection. Many advanced methods are available such as genetic algorithm, clustering based technique, clonal selection for band selection. SDA is comparatively a simpler method and hence is being used by many researchers (Jain et al., 2007; Lucas et al., 2008; Ray et al., 2010; Van Aardt and Wynne, 2001). In present study SDA could identify 22 bands for the discrimination of 8 vegetation classes of tropical deciduous forest. Resulst are comparable with the results obtained by Thenkabail et al. (2004) where combination of band selection mechanism (including SDA) recognised 22 optimal bands for the classification of African savanna vegetation. SDA results clearly depict importance of SWIR region for the discrimination of tropical deciduous forest. Earlier, Clark et al. (2005) reported better crown scale separability of tropical rain forest trees in SWIR region. Chan and Palinckx (2008) reported larger number of bands in SWIR region contributing to the separability of temperate tree species. The SWIR region was observed to be important in the characterization of savanna tree species (Dudeni et al., 2009). Findings of present study are in tune with these reports. Previous studies have shown that the SWIR region has higher correlation with water thickness and plant moisture content (Hardisky et al., 1983; Yilmaz et al., 2008; Delalieux et al., 2009). Hyperion image used in present study was acquired at the time of the year when vegetation in the study area has lush green foliage. This could be the reason for greater separability in the bands coming from SWIR region.

4.4.2 Different classification algorithms

Identifying suitable classification algorithm for hyperspectral data is very important. Classifiers with higher complexity are potentially more effective than the ones with smaller complexity, especially for difficult classification problems (Dalponte et al., 2009). Many advanced classification approaches were used for classification of vegetation, such as Artificial Neural Networks (ANN) (Erbek et al., 2004; Foody, 2004; Kavzoglu and Mather, 2004), Decision tree classifier (Lawrence et al., 2004; Pal and Mather, 2003), Support Vector Machine (SVM) classifier (Dalponte et al., 2009; Melgani and Bruzzone, 2004; Plaza et al., 2009), Random forest and Adaboost (Chan and Palinckx, 2008), linear discriminant analysis (Du and Ren, 2003; Clark et al., 2005), Spectral Angle Mapper (SAM) (Christian and Krishnayya, 2009; Clark et al., 2005). The performance of three classifiers (ANN, SVM and SAM) was compared over highly diverse tropical forest in present study.

Artificial Neural Network (ANN) is the most widely used model. This algorithm is a promising technique for a number of situations such as non-normality, complex feature spaces and multivariate data types, where traditional methods fail to give accurate results (Atkinson and Tatnall, 1997). One of the most notable feature about a neural network which motivates its adoption is its ability to generalize input (Bischof, et al., 1992; Paola and Schowengerdt, et al., 1995; Weeks and Craston, 1997). Large complexity associated with the network structure is the major disadvantage of ANN algorithm. Melgani and Bruzzone (2004) pointed out the effectiveness of Support Vector Machine (SVM) to analyze hyperspectral data directly in the hyper dimensional feature space, without the need of any feature reduction procedure. They also mentioned about the advantage of SVM in classifying heterogeneous data (like the one of tropical system) for which only few training samples are available for each identified class. Shafri et al. (2007) said that core advantage of Spectral Angle Mapper (SAM) is, when used on calibrated reflectance data, it is relatively insensitive to illumination and albedo effects.

4.4.3 Supervised classification

Supervised classification was performed using selected 22 bands and all 165 bands. Performance of three classifiers tested on the spectra coming from 22 bands was different. ANN fared better compared to other two classifiers. The Hyperion image classified with the help of ANN appeared very close to the actual distribution of vegetation seen in the study area. Chan and Palinckx (2008) reported OAA values of 69 % and 70% for the classification of trees and grasslands respectively with the help of two ensemble classification algorithms (Random forest and Adaboost). Martin et al. (1998) reported an OAA of 75% for the classification of 11 forest cover types of conifer species with the help of airborne hyperspectral data. OAA values reported here from ANN classifier are much better than these reports. Lucas et al. (2008) have classified mixed species forests with an accuracy of 87% in central south-east Queensland (Australia) using airborne hyperspectral data. Dalponte et al. (2009) studied a forest area in Italy characterized by 23 different classes reaching accuracies of about 90% with airborne hyperspectral data. Clark et al. (2005) obtained highest accuracy of 92% for crown scale separability of tropical rain forest trees with the help of airborne hyperspectral data. In this study Hyperion data (EO-1) has been used to classify tropical vegetation. OAA levels are appropriate for spaceborne data.

Clear gains in OAA were made using ANN for the mapping of 8 tropical vegetation classes in comparison to SVM and SAM classifiers. The ANN classifier was able to classify correctly even those quadrats which are having lesser percentage of occupancy of a particular vegetation class. ANN gave better OAA for all types of vegetation classes with diverse levels of occupancy. Earlier, Linderman et al. (2004) have reported that the neural network is probably more capable of classifying minor features, adapting to the variable influences of changing canopy conditions. Classification results of this study are analogous to this report.

SAM classifier was unable to correctly classify quadrats having lesser percentage of occupancy. Performance of SAM classifier did not alter for the spectra coming from 22 bands or from 165 bands. SAM classifier fared better in classifying trees with higher percentage of occupancy. This is seen in the accuracy levels of *Tectona* and *Dendrocalamus*. These two species are dominant in the study area with homogenous distribution. Okin et al. (2001) reported failure of multiple endmember spectral mixture analysis in classifying vegetation below 30% occupancy in arid and semiarid environments of southeastern California. Results coming from SAM classifier are in tune with this report. The SAM classifier was least successful of the tested classifiers. Clark et al. (2005) has reported that SAM was unable to achieve high classification accuracies for tropical rain forest trees. Results for SAM classifier are similar to these findings.

SVM classifier tested with 22 band data and 165 band data showed difference in performance. It is worth noting that the kernel based implementation of SVMs involves the problem of selection of multiple parameters (γ, ρ) and the penalization constant (C) (Melgani and Bruzzone, 2004). Selections of appropriate values of these parameters determine the suitability of SVM for a given problem (For detailed information please refer Vapnik, 1995 and Burges, 1998). The idea of standardizing the parameter values is to (i) maximize the margin and (ii) to minimize the estimate of the expected generalization error (Melgani and Bruzzone, 2004). Combinations of parameters with different penalization constants tested here for different classes showed OAA levels falling in a narrow range. OAA values coming from spectra of 165 bands showed higher values and the differences in OAA across various C values are negligible. The best OAA values are coming from C value of 40. Similar values were reported earlier (Melgani and Bruzzone, 2004) for data classification. OAA coming from 22 bands data are lesser while the ones coming from 165 bands are higher and are equivalent to ANN classifier. For the tested data set of this study, performance of SVM was better with 165 bands spectra (without dimensionality reduction). Classified images coming from ANN classifier (22 bands) and SVM classifier (165 bands) are quite similar. Melgani and Bruzzone (2004) pointed out the effectiveness of SVM to analyze hyperspectral data directly in the hyperdimensional feature space, without need of feature reduction procedure. This is reflected in present analysis. Ghiyamat and Shafri (2010) mentioned that discrimination of heterogeneous tropical trees is quite challenging. Different analytical techniques are to be used for better separation. OAA levels obtained in this study by ANN and SVM classifiers identify the suitability of these classifiers for tropical vegetation discrimination.

Findings of present study are encouraging for the discrimination of tropical forest species using space borne hyperspectral data. Earlier, Castro-Esau et al. (2006) stated that the ability to accurately map tree species in tropical ecosystems will represent a significant advancement that will facilitate ecosystem characterization, tree demographic studies, mapping endangered or endemic species, identifying important food sources for wildlife, and quantifying carbon pools and carbon sequestration rates. Results and conclusion of this study can be expanded to address these issues.

4.5 Biophysical attributes

Range of biophysical attributes (quadrat level) obtained from the study area were compared with range of similar attributes acquired from other studies. Results indicated that range of biophysical attributes obtained from the SWS are comparable with other studies in tropical regions. Madugundu et al. (2008) have estimated LAI and biomass of tropical forests of India. Range of LAI and bole biomass in present study is comparable to their findings. Range of LAI values recorded here are comparable with other global level compilations (Soudani et al., 2006: Yang et al., 2006: Ganguly et al., 2008). Estimated LAI values of the study area were compared with MODIS derived LAI product (for 24-10-2006). Range of values was similar. Proportion of area with higher LAI values (>4.5) was higher (16 % in MODIS and 65% in Hyperion) in our estimated product indicating its superiority. Brown et al. (1989), Ponzani et al. (2010) and Englhart et al. (2011) estimated above ground biomass of tropical forests. Range of bole biomass in this study is analogous to these studies. Canopy area values in this study are comparable with the values obtained by Estes et al. (2010) for woody forests of Kenya. All the three covers showed distinction in the values of canopy area indicating specificity of each other. It was maximum in mixed cover followed by teak and bamboo. Complete leaf fall in teak and bamboo (in summer season) left these areas covered with denuded stems.

4.5.1 Partial Least Square (PLS) regression analysis for biophysical attributes

Biophysical attributes (except LAI) were estimated with maximum accuracy when PLS regression models were prepared using full reflectance spectra. PLS model run with narrow spectral range did not give higher accuracy. Earlier, Cho et al. (2007) have concluded that bands selection did not improve performance of PLS regression for predicting herb biomass. Result for bole biomass and canopy area agrees with conclusion made in this study. Wolter et al. (2009) have estimated different biophysical characteristics of coniferous and hardwood species using PLS regression (R^2 values 0.22 to 0.87). Similar range of R^2 values were obtained in present study for biophysical attributes. Goodenough et al. (2006) estimated temperate forest biomass with the help of PLS regression developed using Hyperion data (R^2 =0.82). Coefficient values achieved in present study is comparable to this study. PLS regression analysis revealed that dry season Hyperion data (April) is ideal for the prediction of bole biomass in tropics. Reflectance spectra from April image contain signals mostly coming from defoliated vegetation. This improves accuracy in prediction of bole biomass. Gomez et al., 2011 predicted canopy area of olive trees with R^2 values ranging from 0.65 to 0.82. R^2 values obtained in this study are comparable to this. Spectral region of 1000–1510 nm is found to be more sensitive towards LAI. This confirmed findings of previous studies suggesting a strong relationship between reflectance values at NIR to SWIR bands and LAI (Brown et al., 2000; Cohen and Goward, 2004; Lee et al., 2004; Thenkabail et al., 2004; Schlerf et al., 2005; Darvishzadeh et al., 2008). Earlier, Darvishzadeh et al., (2008) have concluded that the PLS regression did better when subset of related wavelengths were selected for estimation of LAI. Results are in conformity with this study.

Cross validation of the developed PLS regression models with leave one out technique gave better results for both teak and bamboo covers indicating suitability of the model for the determination of measured parameters. To extend the applicability of the model, bole biomass and canopy area of teak were cross matched with the data of mixed vegetation cover. Martens and Martens (2000) mentioned that cross validation between truly independent sample (referred as leave one product out) yields assessment of the ability of the model to reproducibly predict

Y and X via the latent variables, in new samples of the given type. Analysis done in this study gave high R^2 values (0.83 for bole biomass and 0.67 for canopy spread) indicating the applicability of this model for vegetation covers with similar characteristics.

4.6Biochemical attributes

Many important biochemical attributes were considered to increase the comprehensive strength of the study. Measured attributes showed broad range indicating the suitability of the data set for modeling across tropical systems with similar vegetation features. Range of chlorophyll values tested in this study is similar to the ones published by others for temperate / tropical forests and grasslands (Asner and Martin, 2008; le Maire et al., 2008; Darvishzadeh et al. 2008). Range of lignin and cellulose in this study is comparable to the range obtained by Serrano et al., (2002) and Kokaly et al. (2009). Nitrogen range obtained in study is higher than the one reported by Smith et al., (2003); Martin et al., (2008) and Knox et al., (2011). This is attributed to the luxuriant growth of vegetation. EWT measured in present study is comparable to the one used by Ceccato et al. (2002) for spectral modeling studies. This clearly demonstrates the applicability of models coming from this dataset across vegetation covers of tropics with similar composition.

4.6.1 Partial Least Square (PLS) regression analysis for biochemical attributes

All biochemical attributes were estimated with high accuracy when PLS regression was performed with full spectra (except for lignin and cellulose contents of bamboo). Obtained R^2 and Standard Error for Calibration (SEC) / Standard Error for Cross Validation (SECV) values are comparable with published reports (Smith et al., 2002 and 2003; Cho et al., 2007; Asner and Martin, 2008; Martin et al., 2008; Darvishzadeh et al, (2008); Schlerf et al., 2010). Dimensionality reduction is an important aspect in hyperspectral data analysis. Development of any model using full reflectance spectra is time consuming. Secondly, it falls short in exploiting sensitive regions of reflectance spectra. Model performance gets improved when spectral range to be tested is narrowed down to the vicinity of sensitive band/ bands of an identified attribute. This improvises information retrieval specific to a parameter of interest within narrow spectral range. To improve the predictability of the PLS model, spectral subset analysis was carried out. Range of the spectral subset primarily came from published sensitive wavelengths for each attribute recorded here (Curran, 1989; Kokaly et al. 2001; Serrano et al., 2002; Thenkabail et al., 2004; Asner, 2008; Asner and Martin, 2008; Martin et al., 2008). PLS regression results improved when spectral ranges for each parameter were selected. Improvement is seen in R^2 and SEC values. It has been reported that wavelength selection enhances PLS regression results (Davies, 2001; Kubinyi, 1996; Martens and Martens, 2000; Schmidtlein and Sassin, 2004; Darvishzadeh et al., 2008). Results are analogous to these studies. Results of this study reaffirm the importance of 600-750 nm regions for the prediction of chlorophylls. Earlier, Sykioti et al. (2011) reported high sensitivity of 550-750nm spectral region towards stand level chlorophyll content. Asner and Martin (2008) found that chlorophyll contributes more at the spectral region of 510-730nm. Similarly, Gitelson et al., (1996) concluded that maximum sensitivity of chlorophyll concentration appears in the reflectance from 520-630 nm and also near 700 nm. Results for chlorophyll are in confirmity. le Maire et al., (2008) have tested developed indices for chlorophyll estimation in broad-leaved temperate forest stands at canopy scale where variation in measured chlorophyll values were less. Accuracy values in this study are relatively better across a broad range of values. Spectral region of 984-2000 nm is found suitable for nitrogen. It showed higher accuracy in estimating nitrogen for teak and bamboo. Martin et al. (2008) found sensitivity of this spectral region (984-2173 nm) in the estimation of canopy nitrogen across wide range of ecosystems. Findings of this study are in confirmity. Huang et al. (2004) performed PLS regression analysis on air borne hyperspectral data for estimation of nitrogen from *Eucalyptus melliodora* (R^2 =0.75 and RMSE = 6% of mean). Prediction errors (ranging from 19.67 to 22.76 % of mean) obtained in this study are appropriate as they are coming from space borne data. Result showed that spectral subset in SWIR region is highly sensitive towards lignin and cellulose of canopy and stem of teak and bamboo. This confirmed findings of previous studies suggesting a strong relationship between reflectance values at SWIR bands and contents of lignin and cellulose (Curran, 1989; Serrano et al., 2002; Ustin et al., 2004; Thenkabail et al., 2004; Kokaly et al., 2009). Differences seen in the best performing spectral subsets for cellulose and lignin are negligible.

This may be due to spectral similarity between lignin and cellulose (Ustin et al., 2004). Earlier, Serrano et al., (2002) predicted canopy lignin from chaparral vegetation with the help of air borne hyperspectral data (R^2 0.81 and RMSE 23% of mean). Prediction error range obtained in this study is better (19.67 to 22.76 %). EWT did not respond well to subset analysis. It gave maximum accuracy when PLS regression was developed with full Hyperion spectra. Ceccato et al. (2001) have concluded that combination of SWIR and NIR is necessary to retrieve EWT. Sims and Gamon (2003) said that for retrieval of canopy water, wavelengths that are weakly absorbed (NIR bands) are essential as they penetrate more deeply into canopies. These could be the reason for lesser response of EWT to subset analysis. Colombo et al., (2008) predicted canopy EWT by using simulated reflectance spectra (R^2 = 0.85, RMSE 22 %). Error values obtained for retrieval of EWT are similar in this study (21.62 % to 24.93 %).

PLS regression with 165 band spectra and with spectra developed from a narrow range broadly indicates that spectral subset is appropriate for the band sensitive biochemical parameters. For parameters like biomass, canopy cover whole spectrum gives better estimation.

4.7 Development of vegetation indices

4.7.1 Index developed for chlorophyll

PLS regression model for prediction of chlorophyll showed maximum negative coefficient at 692nm and maximum positive coefficient value at 743nm for both Teak and Bamboo. These two wavelengths (692 and 743nm were selected for developing ratios for chlorophyll estimation). Earlier, Cho et al. (2008) suggested that wavebands at 680, 694, 724 and 760 nm have the potential for maximally explaining variations in leaf chlorophyll content with minimal effects of leaf and canopy biophysical confounders such as LAI. Simple ratio (743/692) gave best results for prediction of chlorophyll with Leave One Out Cross Validation (LOO-CV). Wu et al. (2010) evaluated Hyperion data for chlorophyll content estimation with a range of vegetation indices. The lowest RMSE reported in their study was 30.53 % of mean. RMSE values of this study (RMSE 9.49-16.57 % of mean) are lower for both the species mentioning about higher accuracy of the developed ratio in chlorophyll estimation. Predictive errors (for chlorophyll estimation) obtained for the two tropical species (teak and bamboo) in present study is similar to the ones reported by le Maire et al. (2008) in temperate forest stands using Hyperion data.

4.7.2 Index developed for LAI

PLS regression performed on spectral region of 1000-1507 nm gave the best results. Further separation of spectral subset into narrow spectral regions and subsequent PLS analysis failed in making any more improvement of prediction error for LAI. Earlier, Darvishzadeh et al. (2008) predicted LAI using PLS regression analysis at canopy level using airborne spectra (Root Mean Square Error, RMSE 11.59 % of mean). Prediction results for LAI are better than this study. Results suggested that broad spectral region of 1000nm–1507nm is sensitive towards LAI. This confirmed findings of previous studies suggesting a strong relationship between reflectance values at NIR to SWIR bands and LAI (Brown et al., 2000, Cohen and Goward, 2004, Lee et al., 2004, Thenkabail et al., 2004, Schlerf et al., 2005). The best PLS regression model for prediction of LAI showed maximum negative coefficient at 1457nm and maximum positive coefficient value at 1084nm. This coincides with the findings of Schlerf et al., (2004, 2005) mentioning the importance of 1088nm for the estimation of LAI. These two wavelengths (1084 and 1457 nm) were selected to develop ratios for LAI estimation. Normalized difference ratio (ND1457/1084) gave the best results for prediction of LAI with LOO-CV method (R^2 0.66, RMSE 0.57). Wu et al., (2010) evaluated Hyperion data for LAI estimation using various vegetation indices. The lowest RMSE reported in their study was 32.73 % of mean. In this study predicted LAI with the help of vegetation indices resulted with a lower RMSE value 13.57 % of mean. Prediction errors obtained in this study are better than the ones reported earlier by Wu et al., (2010) and le Maire et al., (2008).

Three vegetation covers (teak, bamboo and mixed vegetation) showed high variation in the levels of different biophysical and biochemical attributes. These differences are detectable and can be used to map vegetation. Results emphasize the importance of spectral and temporal variations in quantifying biochemical and biophysical attributes of a tropical dry forest. PLS analysis fared well in estimating biochemical attributes with spectral subset. Whole spectrum (of 165 bands) did better for biomass and canopy area estimates. R^2 values reported here are highly appropriate as they are coming from space borne data. PLS analysis of this study can be extrapolated to other regions having predominant coverage of teak and bamboo.

Historically, the potential of remote sensing for ecological studies remained limited for a variety of reasons, including the insufficient spatial, spectral, or temporal resolution of most remote sensing data (Gamon, 2008). Results of this study illustrate that the space borne hyperspectral remote sensing presents a wealth of possibilities for expanding understanding of tropical ecosystems. Earlier, Blackburn and Milton, (1995) stated that hyperspectral technology would allow for more accurate quantification of forest biophysical and biochemical attributes, which is essential for biodiversity assessment, land cover characterization, biomass modeling, and carbon flux estimation. Results obtained in present study support these views. Ecosystem information (forest biophysical and biochemical attributes) obtained in resent study can be used in forest disaster detection, species mapping, Kyoto Protocol information products, monitoring forest health, ecosystem protection, and global change. Results obtained in present study have provided a platform for measurement of spatial variation of plant pigments accurately using space borne hyperspectral data. Earlier, Blackburn (2006) said that information concerning the temporal dynamics and spatial variations of plant pigments can provide key contributions to a wide range of scientific investigations and environmental/agricultural management endeavors. Observations of present study can be extended to these lines.

4.8 Laboratory spectra

Considerable variation in reflectance at NIR and SWIR regions of electromagnetic spectrum was observed between average leaf level laboratory reflectance spectra of teak, bamboo and other mixed vegetation tree species. Similar pattern of variation was observed in leaf level spectra of seven tropical tree species by Clark et al.

(2005). They stated that several factors can cause leaf spectral variation within a given species, including leaf thickness, necrosis, maturation of the mesophyll, and the concentration of chlorophyll and water. In present study it was observed that increase in leaf thickness values cause increase in reflectance of NIR region. Many studies reported that the NIR spectral range is dominated by variation in leaf water content and leaf thickness, related to specific Leaf area (SLA) (Thomas et al., 1971; Hunt et al., 1987; Jacquemoud and Baret, 1990; Ceccato et al., 2001). Thin leaves are compact and have fewer air-cell wall refractive discontinuities causing lower NIR–SWIR reflectance (Gausman, 1985). Results in present study clearly illustrated the relationship between number of palisade layer and reflectance in NIR region. Earlier, Ourcival and Joffre (1999) reported that palisade mesophyll and total thickness were strongly correlated with reflectance spectra. Vogelmann and Martin (1993) showed that long, cylindrical palisade mesophyll cells propagate visible wavelengths deeper into the leaf interior, whereas the more spherical spongy mesophyll cells tend to scatter radiation. Present study tried to establish relationship between leaf structure and reflectance. Earlier, Slaton et al., (2001) stated that this relation between leaf structure and reflectance may be useful in the interpretation of remote sensing data measured from satellite or aircraft, or with standard field and laboratory instrumentation. Variation in the SWIR region is caused by leaf water concentration, with important contributions from protein N, cellulose and lignin (Curran,1989).

SDA identified 10 wavelengths from laboratory spectra of five selected species showing variation in reflectance values. Of the 10 identified wavelengths, five came from visible region, three from NIR region and two bands from SWIR region. The most frequently selected wavebands in present analyses were in the blue-green region (410,520,550, nm) and red region (630,670 nm) of electromagnetic spectrum. These findings are similar to Fung et al. (1999), who used stepwise linear discriminant analysis for feature selection and found selected bands to lie mainly in the green peak and red edge regions. However, the bands selected depend on the data used and therefore differ from one suite of species to the next to optimize separability in each case.

Range of total chlorophyll (leaf level) values tested in this study is similar to the ones published by le Maire et al. (2004) and Zarco-Tejada et al. (2004), for different broad leaf tree species and few open canopy tree crops respectively. Range of chlorophyll a and b values (leaf level) is similar to range provided by Cao (2000) from leaves of few tropical woody tree species. Results indicate that red edge index developed by Vogelmann et al. (1993) , ZTM index developed by Zarco Tejada et al. (2001) and Red Edge index 750~700 developed by Gitelson and Merzylak (1997) gave better results for estimation of both total chlorophyll and chlorophyll a. All the three vegetation indices were calculated from the reflectance coming from red edge region (680–750 nm) (Horler et al., 1983; Filella and Penuelas, 1994). In this study testing of different indices reaffirmed the importance of REP for estimation of total chlorophyll and chlorophyll a.