

Original Research Article

Estimation of Biomass and Leaf Area Index in the Western Ghats' Forest Ecosystem by the Integrated Analysis of Hyperspectral Data and Space Borne LiDAR Data

ABSTRACT

The Western Ghats regions of India are characterised by highly complex and biodiverse forest ecosystem with heterogeneous tree species. Traditional multispectral remote sensing, due to its poor spectral information and lower number of bands do not allow a detailed analysis of tree species. The integration of LiDAR data with multispectral remote sensing has limitations in the case of spectral information abundance. The given study presented a new approach by the integration of space borne LiDAR with hyper spectral imagery for the estimation of biomass and Leaf Area Index in the Western Ghats regions. The main objective of the given study is the biophysical characterisation in the Western Ghats regions of India by the integration of GLAS ICESat data and AVIRIS hyperspectral data. The structural characteristics extracted from the LiDAR data are integrated with spectral characteristics from the AVIRIS NG imagery based on the pixel level so that biophysical characters including canopy height, biomass, Leaf Area Index are estimated. The integrated product on further analysis revealed the applicability of this approach to extract more spectral information and forest parameters. The results indicated that integration of LiDAR with AVIRIS data enabled forest species discrimination and biophysical parameter retrieval successfully with abundant spectral information than in the case of multispectral imagery. **Please add conclusion in one sentence at least**

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Keywords: GLAS, ICESat, Hyperspectral, Biophysical Parameters, Leaf Area Index, Biomass

1. INTRODUCTION

The Western Ghats of India is characterised by complex forest ecosystems with large varieties of heterogeneous tree species. Mudumalai and Sholayur are two reserved forests in Western Ghats region. These forests represent a diversity of habitats that vary both spatially and temporally. Spatial variables are influenced by the factors such as soils, climate, geology, topography and the species distribution. Temporal variables are influenced by climate and hydrology. The measurement of biophysical parameters in the complex ecosystem of Western Ghats of India is a challenge in the case of forest measurements. Biophysical parameters in the forest ecosystem comprise of structural as well as spatial parameters. Of these the structural parameters include canopy height, canopy cover, tree heights, density and the spectral parameters of the forests include different vegetation indices, biomass etc.

Traditional field inventories for the extraction of biophysical parameters are found to be time consuming and have both spatial and cost constraints. Remote sensing technologies have found to overcome the limitations of field inventories in the case of cost, spatial coverage and regular collection of data. Remote sensing technologies including the photogrammetric methods and the multispectral images are capable of measuring can measure the spectral parameters to some extent. Multispectral remote sensing has lot of applications in estimating the horizontal and spectral attributes of forests [1],[2],[3],[4],[5]. But they are limited in the case of measuring structural attributes [6],[7],[8]. For measuring the structural attributes, active remote sensing technology mainly Light

46 | Detection and Ranging (LiDAR), proved to be successful by measuring the ~~threedimensional~~three-
47 | dimensional structure of forests. Several studies showed the applicability of LiDAR in the estimation of
48 | structural parameters like canopy height, density, tree heights etc[9],[10],[11].However, in all these
49 | cases, lack of spectral information is a limitation. For estimating both the structural and the spectral
50 | attributes of forest ecosystem integration of LiDAR data along with the optical remote sensing is
51 | possible. Several studies showed the estimation of biophysical parameters by the fusion of optical as
52 | well as LiDAR data. But the multispectral remote sensing is limited by the number of bands.

53 | Forest management must be interdisciplinary and multiscale. In the complex forest ecosystem
54 | of Western Ghats with high level of biodiversity and spatial heterogeneity, species identification is a
55 | challenge. Thick understory vegetation also contributes to the species diversity of Western Ghats.
56 | Hyperspectral data which have abundant spectral content have potential to measure the complex
57 | forest ecosystems and identification of individual tree species along with fine spectral and spatial
58 | details[12],[13]. Several studies have been reported the application of hyperspectral imagery in
59 | forestry[14].Optical indices which are sensitive to both chlorophyll content and canopy structure are
60 | useful in understanding whether the forests are healthy or stressed, forest decline, for modelling
61 | forest nitrogen content, leaf economic spectrum and leaf development [15],[16],[17],[18],[19],[20].
62 | Hyperspectral remote sensing can acquire very narrow typically 200 or more bands thus obtaining
63 | contiguous reflectance bands for every pixel in the ~~scene~~scene [21], thereby enabling in depth
64 | analysis of the forest species. On integrating the hyperspectral imagery with LiDAR structural as well
65 | as biophysical parameters can be extracted, and several studies reported successful results. The
66 | integration approach is used for biomass estimation [22], and classification of complex forest
67 | areas[23]. For modelling plant composition in a forest landscape [24] and mapping multiscale vascular
68 | plant scape richness, Hakkenberg et al [25] integrated LiDAR and hyperspectral remote sensing.
69 | Forest fuel characteristics in pine forests can be estimated by integrating airborne laser scanner and
70 | hyperspectral imagery[26]. Based on the available literatures, forest parameters estimation along
71 | with the forest health conditions and the identification of individual trees in Western Ghats region is
72 | possible by combining the applications from the hyperspectral and LiDAR sensors.

73 | Full waveform LiDAR can estimate the forest parameters in detail compared to the discrete
74 | airborne LiDAR systems. The first space borne full waveform LiDAR system was developed by NASA,
75 | which is the Geoscience Laser Altimetry System (GLAS) on board by Ice and Cloud Land Elevation
76 | Satellite (ICESat) in January 2003.The diameter of GLAS waveform foot print is 70m with 172m
77 | spacing and have found applications in various earth science fields. GLAS LiDAR data have so many
78 | applications in the case of forest canopy modelling and measurements. A lot of work were done using
79 | GLAS data in forestry[27],[28],[29],[30],[31],[32],[33],[34],[35].GLAS can provide accurate estimates of
80 | canopy heights, biomass, canopy density, above-ground biomass and overall the three dimensional
81 | forest modelling with high levels of precision. In most forest studies the GLAS system was used for
82 | the forest structural measurements [36],[37],[38],[39],[40],[41]. In this study, an attempt has been
83 | made to estimate the biophysical parameters in the heterogeneous forest in Western Ghats by
84 | integrating the AVIRIS -NG imagery with the space borne LiDAR data.

85 | The main objective of the work is the extraction of biomass and Leaf Area Index(LAI)by the
86 | integration of AVIRIS-NG imagery with ICESat GLAS data in the Mudumalai and Sholayur forests of
87 | Western Ghats, India. The integration of LiDAR data with high resolution airborne hyperspectral
88 | imagery narrow band features can offer enhanced spectral information on integration with LiDAR
89 | point cloud.

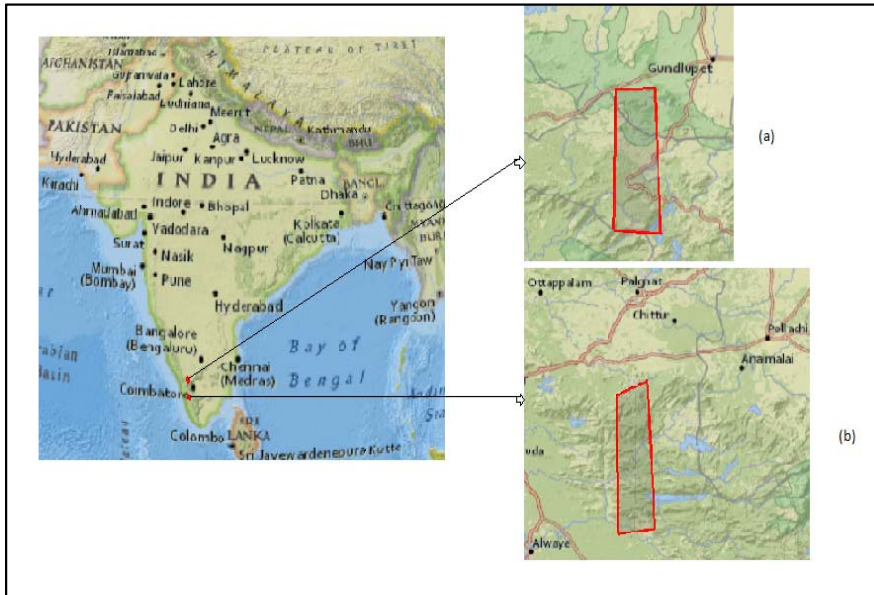
90 | **2. Materials and Method**

91 | **2.1.STUDY AREA**

92 | Mudumalai and Sholayar reserved forests are selected as the study area. They are the parts
93 | of the Western Ghats region. Mudumalai region is in Tamilnadu, with an area of $411Km^2$ and this

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94 forest region comprises of and the type of forests is of tropical moist deciduous, dry deciduous, semi
 95 evergreen and thorn forests and having an annual rainfall of range 1700mm. Dominant species in the
 96 study area Mudumalai are *Anogeisuslatifolia*, *Terminalia alata*, *Grewiatilifolia*, *Mangiferaindica*,
 97 *Shorearoxburghi*, and *Tectonagrandis*. Sholayar 368 Km²comprises of tropical evergreen forests with
 98 an annual rainfall of 3780mm and this forest region is in Kerala.The Figure 1 depicts the study area.



99

100 **Fig.1. Study area a) Mudumalai forest and b) Sholayar Forest**

101 **32.2. DATA SETS USED**

102 Two data sets are used in the study:-

- 103 1. Airborne hyperspectral imagery
- 104 2. Space borne LiDAR data

105 Please, add the physical soil analysis for study area at least from references if you didn't
 106 measured

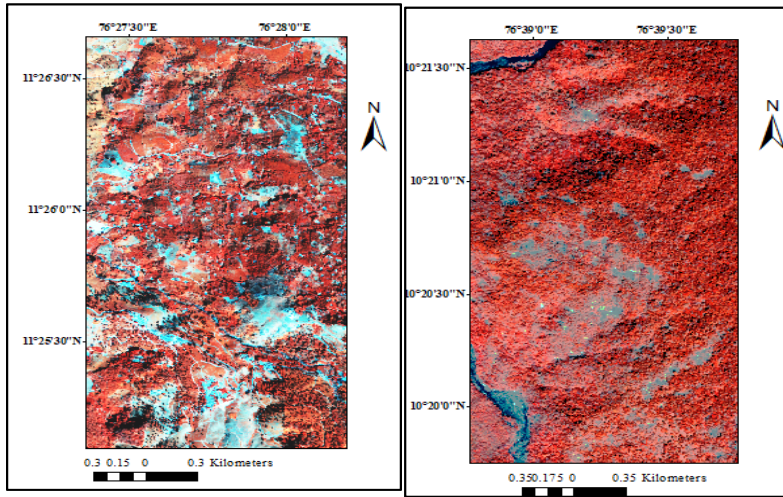
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107 ~~3.1~~ **2.3. Airborne hyperspectral imagery**

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108 Airborne Visible and Infrared Imaging Spectrometer-Next Generation (AVIRIS-NG) of JPL (Jet
 109 Propulsion Laboratory), NASA, has been used for the ISRO-NASA airborne campaign on-board an
 110 ISRO B200 aircraft. There are about 430 narrow continuous spectral bands in VNIR and SWIR
 111 regions in the range of 380 –2510 nm at 5nm interval with high SNR (>2000 @ 600 nm and >1000 @
 112 2200 nm) with accuracy of 95% having FOV of 34 degree and IFOV of 1mrad. Ground Sampling
 113 Distance (GSD) vis-à-vis pixel resolution varies from 4 –8m for flight altitude of 4 –8 km for a swath of
 114 4-6 km. AVIRIS-NG for Sholayar and Mudumalai are collected during the first phase (January 2016) is
 115 the data set used in this study. For Sholayar region level 1 (L1) data is used which represent raw
 116 data, calibrated and ortho-rectified top-of-radiance (TOA), respectively which were generated on-
 117 board the aircraft. For Mudumalai region both L1 and L2 (surface reflectance products in all the bands
 118 after atmospheric correction) are used. The data after atmospheric correction and radiometric
 119 calibration were converted to reflectance measurements for further analysis. The AVIRIS data sets
 120 after atmospheric corrections for Mudumalai and Sholayar are shown in Figures 2 and 3 respectively.

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122 **Fig. 2. AVIRIS -NG data sets for Mudumalai_forest Fig. 3.AVIRIS- NG for Sholayarforest**

123

124 **3.22.4 Space borne LiDAR data**

125 GLAS ICESat laser altimetry data isobtained from the ICESat/GLAS NSIDC website and are
 126 pre-processed by means of ICESat /GLAS tools. Product 14 is used here which contains surface
 127 elevations and elevation corrections.The data sets are filtered by using available quality flags for
 128 saturation, presence of cloud and validity of elevation.

129 **4.3. METHODOLOGY**

130 The methodology used in the study is depicted in the Figure 4.

131 **4.3.1 Pre-Processing of spaceborne LiDAR data**

132 From the GLAS LiDAR point cloud data digital elevation models and surface models are
 133 generated which by normalization gives canopy height models for both the regions.

134 **4.3.2 Pre-processing of AVIRIS - NG imagery**

135 For radiometric calibration, atmospheric correction module named Quick Atmospheric
 136 correction (QUAC) is done for the AVIRIS-NG imagery for both study area thereby creating surface
 137 reflectance images.

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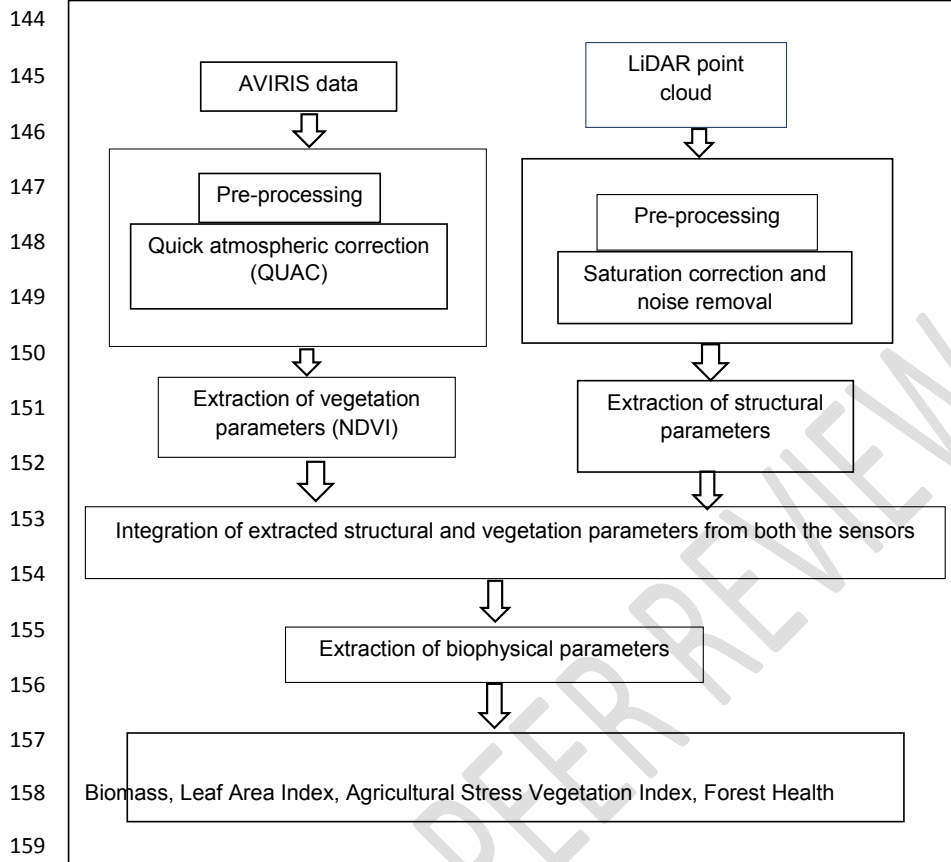
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160 **Fig.4. Flowchart depicting methodology**

161

162 **4.3.3 Integration of LiDAR point cloud and hyperspectral imagery**

163 The point cloud-based canopy height models are integrated with hyperspectral imagery based
 164 spectral indices on a pixel level fusion strategy after linearly stretching the imageries incorporating for
 165 each pixel in the hyperspectral imagery.

166

167 **4.4 Estimation of biophysical parameters**

168 Canopy heights are directly estimated from the LiDAR point cloud by the analysis of the
 169 waveform LiDAR data. Forest biomass cannot be directly estimated from the LiDAR data or the
 170 hyperspectral imagery. In the given work, forest biomass is estimated by Support Vector Machine
 171 predictive algorithm from the integrated image by using Radial basis function as the kernel function
 172 and Laplacian function as the loss function for handling the non-linearity among the input features.
 173 Agricultural stress vegetation indices are calculated by using the vegetation indices in the broadband,
 174 narrowband, light use efficiency, canopy nitrogen, leaf pigment and canopy water content categories
 175 and created a spatial map showing the distribution of canopy stress. Forest health is also calculated
 176 by using the vegetation indices in the broadband, narrowband, light use efficiency, leaf pigment and

177 canopy water content and created a spatial map showing the overall health and vigour of the two
178 study area. Leaf area index is obtained for both the study area by using the equation

179
$$LAI = 3.618 * EVI - 0.118 \quad (1)$$

180 where EVI is the Enhanced vegetation indices. LAI for both the regions can estimate the foliage cover
181 and forecast canopy growth and yield

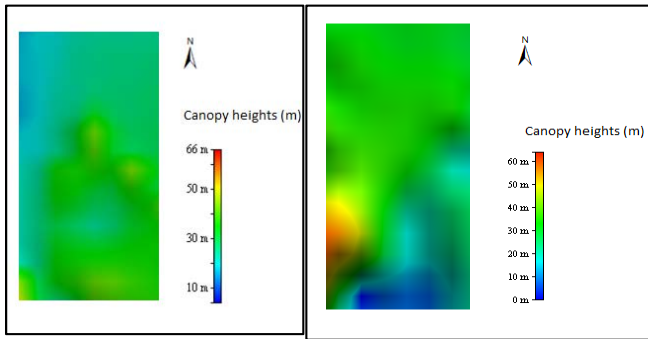
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183 **5.RESULTS AND DISCUSSION**

184 **5.1 Estimation of structural and spectral biophysical parameters**

185 Canopy height model for the Sholayar and Mudumalai region is shown in the Figure 5 and 6
186 respectively. The Canopy height models indicates the height distribution of the study area along with
187 the understory vegetation heights. From the canopy height model, the canopy height of Mudumalai
188 varies from 1m to 60m and for Sholayar, its 1m to 66m.

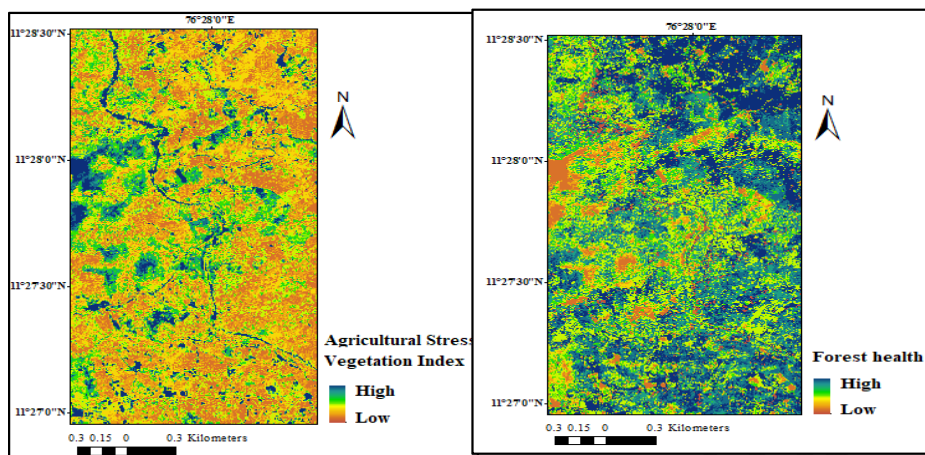


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190 **Fig. 5. Canopy height model for Sholayar Fig.6. Canopy height model for Mudumalai Forest**
191 **Forest**

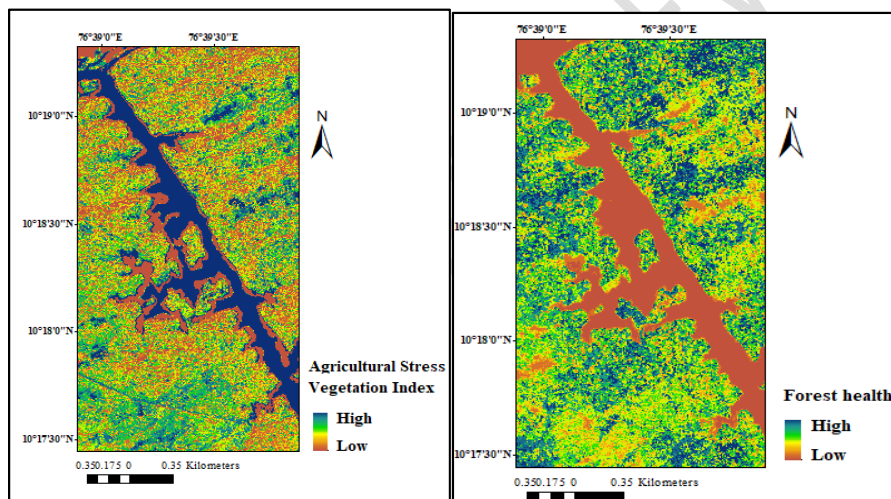
192 The agricultural stress vegetation indices and the forest health distribution for Mudumalai and
193 Sholayar are shown in the Figures 7 and 8. From the Figures growth efficiency can be estimated
194 since the dying species do not efficiently use nitrogen and light indicating the forest stress. Where as
195 the tree species showing healthy, productive vegetation indicates low stress. The agricultural stress
196 vegetation indices divided the study area into classes ranging from lowest stress to highest stress.
197 Forest health distribution detected pest and blight conditions of Mudumalai and Sholayar and for
198 assessing area of timber harvest. Healthy forest areas showed low stress conditions in the figure
199 whereas the high stressed forest indicated in the study area shows the signs of dry, sparse canopy
200 and inefficient light use.

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202

203 **Fig. 7. Agricultural stress vegetation indices and forest health for Mudumalai forest**

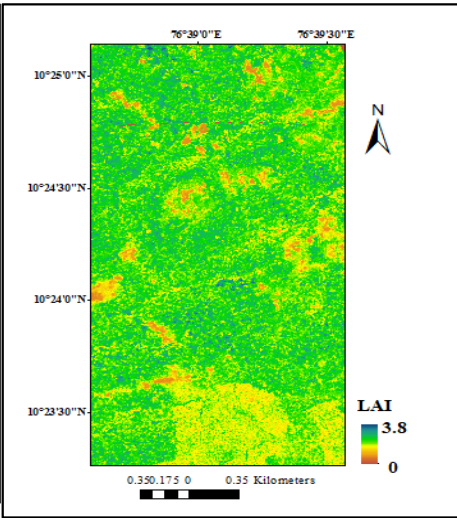
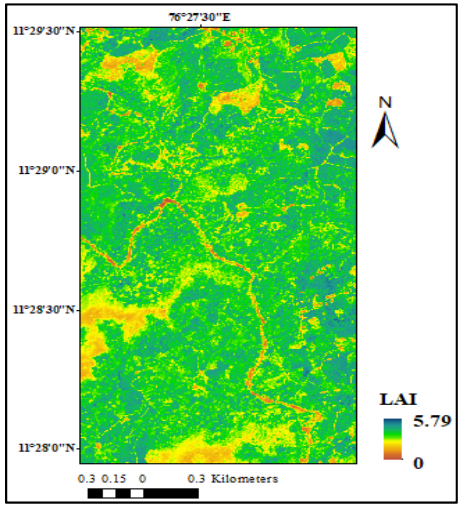


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205 **Fig.8. Agricultural stress vegetation indices and forest health for Sholayar forest**

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207 The estimated LAI for Mudumalai and Sholayar forest is shown in Figures 9 and 10. The value
208 of LAI for Sholayar has a maximum of 3.8 and Mudumalai has a maximum of 5.79.



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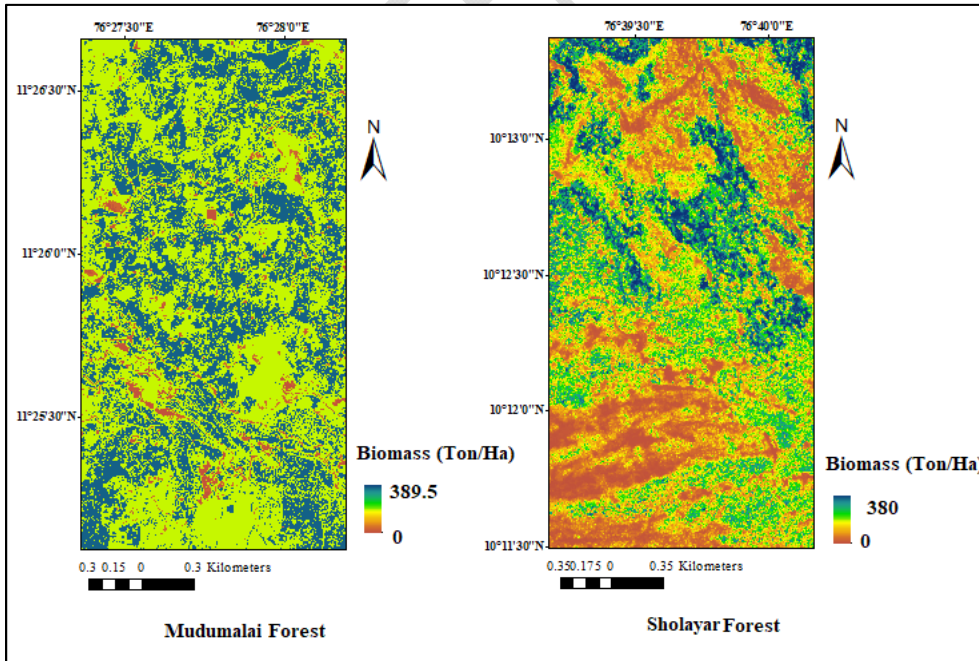
210 **Fig.9. Leaf Area Index for Mudumalai forest**

210 **Fig.10. Leaf Area Index of Sholayar forest**

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212 Biomass estimated for Mudumalai and Sholayar is indicated in the Figure 11. The maximum
 213 value of biomass of Mudumalai region is 389.5 Ton/ha and for Sholayar the value is 380Ton/ha.

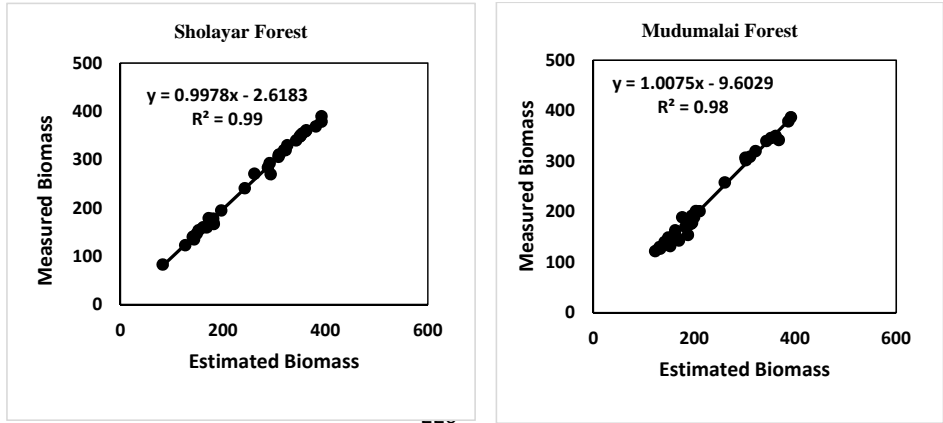
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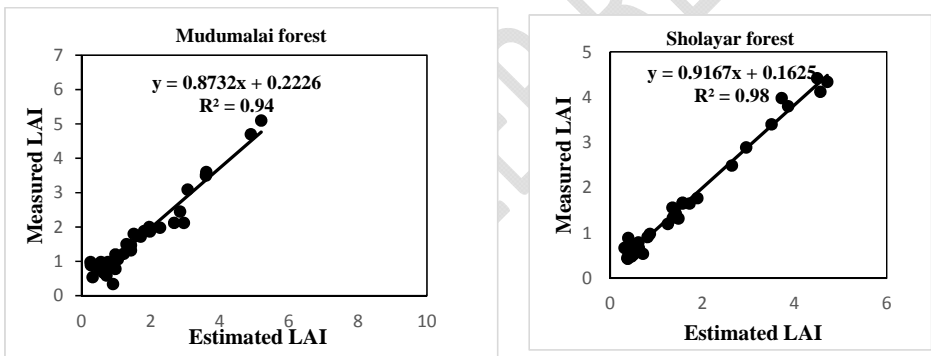
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216 **Fig. 11. Biomass of Mudumalai and Sholayar**

217 The biomass and LAI are compared with the field measured values over the two study area
 218 for the same period and is found to have strong correlation. Scatter plot showing the variation of LAI
 219 and biomass with the field based measurements are shown in the Figures12 and 13.



221 **Fig.12. Scatter plot showing estimated biomass verses field based biomass for Sholayar and**
 222 **Mudumalai forest**



223
 224 **Fig. 13. Scatter plot showing estimated biomass verses field based biomass for Mudumalai**
 225 **and Sholayar forest**

226
 227
 228 The study extracted the biophysical parameters in the Western Ghats effectively. In the
 229 regions with lower value of LAI and biomass, degradation of forest is indicated. But in the regions with
 230 higher value of biomass, presence of thick canopy along with understory vegetation is seen. Canopy
 231 of height ranging from 10m -45 m are seen here based on the CHM created by GLAS point cloud.
 232 Agricultural stress and the forest health indices successfully predictthe health of the forest. The
 233 structural parameters estimated from CHM is applicable in estimating the tree species of the specified
 234 forests. GLAS point cloud data used here enabled to extract the structural parameters in the forests
 235 which cannot be measured by the hyperspectral imagery directly. The integration approach
 236 successfully estimated both structural as well as spectral parameters which is not possible
 237 independently.

238

239 6. CONCLUSION

240 The main conclusions of the study are the following. The integration of LiDAR with the
241 hyperspectral imagery in the Western Ghats regions of India successfully estimated the biophysical
242 parameters. The important biophysical parameters estimated are canopy height, biomass, vegetation
243 stress indices, forest health indices and Leaf area index. Good correlation with the field
244 measurements is obtained for biomass and LAI for both Sholayar and Mudumalai forest. The
245 approach developed in this study enabled to understand the forest health conditions with detailed
246 spectral parameters along with the structural parameters.

247

248 7. COMPETING INTERESTS

249

250 The authors have no competing interests/ conflict of interest to declare.

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