BIOPHYSICAL CHARACTERISATION OF HETEROGENEOUS FOREST AND PHENOLOGICAL STUDY IN WESTERN GHATS OF INDIA BY THE INTEGRATION OF SENTINEL-2 DATA WITH SPACE BORNE LiDAR DATA

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Abstract

Biophysical characterisation and phenological analysis in heterogeneous forests is a challenging effort due to highly complex and biodiverse tropical forest ecosystems. Apart from the traditional and multispectral remote sensing technologies like Landsat imageries, MODIS etc, high resolution Sentinel imagery can contribute significantly in understanding the tropical forest ecosystems phenology, global carbon cycle, productivity of the forests and carbon budgets. Here we propose a methodological approach by the integration of space borne LiDAR data with the Sentinel -2 imagery for the accurate estimation of the biophysical parameters and understanding the phenological patterns in the Western Ghats of India. The structural parameters estimated from the LiDAR data and the spectral parameters from the Sentinel-2 imagery are integrated, and the resultant obtained is processed by means of nonparametric regression-based Support vector machine algorithm. The results obtained are validated and are found to have strong correlation with ground measurements. Additional vegetation parameters because of the spectral enrichment and dense time series Sentinel-2 imagery contribute in understanding significant information of forests including degradation, health status and the complex ecosystems. The study also has the advantage of understanding the understory vegetation conditions of the forests ecosystem which contribute an important help for forests management and practices.

Keywords: ICESat, GLAS, LiDAR, Sentinel-2, Support Vector Machine method, Phenology, Biomass, Biophysical parameters.

1. INTRODUCTION

Phenology is the study of periodicity or timing of biological events which involves flowering, fruiting leaf lushing and germination which has important effect on survival, reproductive success (Leith, 1974; Van Schaik et al, 1993). Tropical forest characterised by high diversity may cause constraints to phenological events in many ways (Newstorm et al, 1994, Janzen, 1978). In tropical forest plants reproduce once in a year and it is substantial to understand the hierarchical aspects of phenological events. (Newstorm et al, 1994). Trees can overcome the soil moisture stress during dry period by developing deep tap roots which can extract ground water (Murali and Sukumar, 1993). Trees can also store water in their conductive tissues for further use during early leaf flushing phase and retaining sufficient moisture (Bullock and Solis-Magallanes, 1990; Brochert 1994) and the trees flushes before the onset of rain, so that leaves can expand rapidly during rainy season. Also, there is adaptation by reducing Leaf Area Index(LAI), when soil moisture is low (Maherali et al, 2004). Ecophysiological observations are needed to understand the phenological variations of tree species with respect to the availability of rain as well as to model the future climate change in the case of tropical forest ecosystem of India. The periodic change in rainfall play a significant correlation with tropical plant phenology (Van Schaik et al, 1993; Reich and Borchert, 1984). In contrast to the temperate forest plants often flower without any regularity and order which are internally regulate (Reich 1995). Phenological studies are substantial for understanding the forest ecosystems in order to elucidate the seasonal patterns of the events. Several studies are done to understand the phenological patterns and its significance in forests. Phenological events in the case of trees have a periodicity ranging from 5-12 months based on the annual humidity variation. Phenological measurements of tropical heterogeneous forests with high degree of species diversity which include the periodicity of flowering, flushing and shedding of leaves, fruiting etc are limited. Phenological leaf flushing is very responsive to the onset of rainfall based on flowering and flushing and cannot be possible at the same time when there is moisture stress. Dry season of tropical forests are characterised by leaf flushing and leaf fall. It is evident that leaf emerge and nurture during high temperature, less rainfall and days with increased duration. Leaf fall occurs when temperature is low and short duration days

(Sundarapandian et al, 2005; Shukla and Ramakrishnan, 1982; Bhat and Murali, 2001). Obviously, leaf abscission which occurs during dry season, also depending on the incident radiation (Singh and Singh, 1992; Borchert et al, 1980). Transpiration is absent and tree store water for subsequent use for the leaf lushing phase of dry months. Also, flower bud activity is high during leaf fall and lush for the months June to April and flower bud activity is less during July August and November. Flower maturation activity is high during February to May and small during September. Fruit initiation is less in March and June and high at March to May and the fruit ripening on May to July.

It is evident that for observing periodicity and seasonality of the year to year variation of phenological events long term monitoring of tropical forests is required. Global environmental change is acritical issue which clearly depicted the significance of long term monitoring of plant phenology. Phenology has tremendous control on terrestrial carbon cycling and sequestration. Comparison of the phenological events in the tropical forests, helps to understand the phenological diversity and the significant changes in the global patterns and process (Corlett and Lafrankie, 1998; Sakai, 2001). To understand the effect of climate on plant and animal population also, accurate monitoring of forest phenology is substantial. Accurate knowledge and understanding of phenological stages are important inputs for studying global carbon cycles and water cycles as well as for modelling climate (Menzel, 2002; Arora and Boer, 2005). Digital cameras are extensively used for monitoring phenology (Moore et al, 2016). Satellite data have been increasingly used to monitor forest phenology because of the long term monitoring and global coverage. Several studies were done based on the medium to coarse resolution satellites for monitoring the phenological events in the forest ecosystems. Landscape level observation of phenology were found to be achieved by MODIS (Reed et al, 1994; Vrieling et al, 2011; Zhang et al, 2003). Vegetation phenology monitoring by MODIS (Zhang et al, 2003), tropical forest phenology in French Guinea from MODIS time series are some of the successful studies. Hufkens et al, (2012) explained the deciduous leaf phenological studies linking near surface and satellite remote sensing. In some studies, observation of phenology by the field based digital photography and satellite data was done (Parihar et al, 2013). These medium to coarse resolution remote sensors can capture the regional and global patterns. But they are limited by the inadequate spatial and temporal resolution which makes it difficult to monitor forest phenology effectively. The atmospheric and sensor associated characteristics also limits the use of satellite data over tropical forest (Laurance, 2004). They cannot properly represent the actual phenological variations of tropical heterogeneous forests (Vrieling et al, 2017). Monitoring of tropical phenology is limited by the unavailability of high temporal and spatial satellite time series data.

With the advent of the Sentinel -2 imagery provided by European space Agency, which has high operational ability, long term continuity, it is possible to obtain free and open source multispectral high spatial resolution images with 13 bands in the optical, NIR and SWIR part of the electromagnetic spectrum. The Sentinel -2 imagery with richer spatial and spectral content (Pesaresi et al, 2016) and therefore has the potential for vegetation mapping and monitoring. Sentinel data can play a significant role in biophysical parameter estimation as well as monitoring the forest phenology by facilitating the monitoring of forests systematically every 5 to 10 days (Veloso et al, 2017). Dense time series data of Sentinel data offers a unique opportunity to systematic monitoring of forests at a weekly repeated cycle with high continuity and long term environmental monitoring. Biophysical parameter estimation in the heterogeneous forests can play substantial role in the forest management and practices. Biomass assessment is very necessary as it is associated with carbon budgets and the global carbon cycle (Hall et al, 1995; Cairns et al, 1997). The estimation of biomass can provide information about the changes in the forest ecosystem due to deforestation, fire, harvesting and climate change (Tan et al, 2007). Biomass and vegetation indices are highly correlated in forest ecosystems (Das and Singh, 2012). Leaf area index Traditional field measurements are found to be time consuming and limited in the case of spatial coverage. Remotes sensing technologies are widely used for estimating the biomass and vegetation indices. Several studies have done for the estimation of biophysical parameters using multispectral satellite imageries including Landsat series (Lu et al, 2004; Karlson et al, 2015; Dube and Mutanga, 2015; Gao et al 2016). However, the use of Landsat series optical imagery is limited in the case of spectral bands, spatial contents and the operational capability.

Sentinel data can provide information regarding temporal variation, behaviour of the variety of tree species including small species. The analysis of Sentinel data can enhance the estimation of biophysical parameters as well as understanding phenology by reproducing the tree phenological cycles and monitor forests in real time basis. Dense time series data allows to capture even short phenological stages and describing the different canopy growth stages. Multispectral Sentinel imagery data is not capable of providing the structural parameters but can only provide the horizontal structure of forests (Hudak et al, 2012; Lefsky et al, 1998). The emerging technology Light Detection and Ranging (LiDAR) provided three dimensional structure of forest including vertical and horizontal structure of forests. LiDAR is found to be used for the canopy heights, canopy density, vegetaion cover etc and several applications in forest measurements. Several studies were done based on the application of airborne LiDAR in the estimation of forest density, biomass and the vegetation parameters.(Wudler et al, 2008; Lee et al, 2011; Andersen et al, 2006; Popescu et al 2003; Lefsky et al, 1999; Tang et al, 2014; Wang et al, 2017). But it is evident from these studies that the airborne discrete return LiDAR have limitations including high cost and limited spatial coverage. The introduction of the space borne full waveform Lidar Geoscience Laser altimetry system onboard Ice sea Land Elevation satellite (ICESat) launched in January 13, 2003, which can provide full wave form LiDAR data with global coverage and large footprint having diameter 70m with 172m spacing can overcome the above limitations. GLAS ICESat data have found applications in measuring the 3D information of forest in global scale. (Zwally et al, 2002; Schutz et al, 2005; Mahoney et al, 2016; Lefsky, 2010; Luo et al 2013). Several studies have done to integrate GLAS data with optical imagery for the extraction of forest attributes. (Wang et al, 2016; Hajj et al, 2017; Liu and Chen, 2013).

The Western Ghats region of India is one of the hotspots of biodiversity which are characterised by highly complex forests environment with large no of tree species and thick understory and overstory vegetation structure. In such complex forest ecosystems, overstory is characterised by woody and non woody tree species. Highest plant richness is regularly be found in understory including shrubs, herbs and moss coverage. Understanding the forest structure and dynamics of Western Ghats is a challenge in the case of forest measurements and practices. Information regarding phenological events in Western Ghats is limited. The present study focused on monitoring the phenological patterns of dominant tree species of tropical forests ecosystem of Mudumalai region of Western Ghats of India by the combination of GLAS and Sentinel-2 Imagery and extraction of biophysical parameters. Forest ecosystem of Western Ghats is highly complex and heterogeneous with thick understory. The integration of the LiDAR data with Sentinel-2 imagery helps to understand the understory vegetation along with the structural as well as spatial biophysical parameters. The methodology used in this study can be used to understand the forest health conditions, degradation as well as forest monitoring, management and practices.

2. STUDY AREA AND DATA SETS USED

The study area (Figure 1) selected is a protected forest in the Western Ghats region of India. Mudumalai forest in Tamilnadu state has an annual rainfall of range 1700mm and the type of forests is of tropical moist deciduous, dry deciduous, semi evergreen and thorn forests. The elevation value ranges from 960 to 1266m for the forest area.

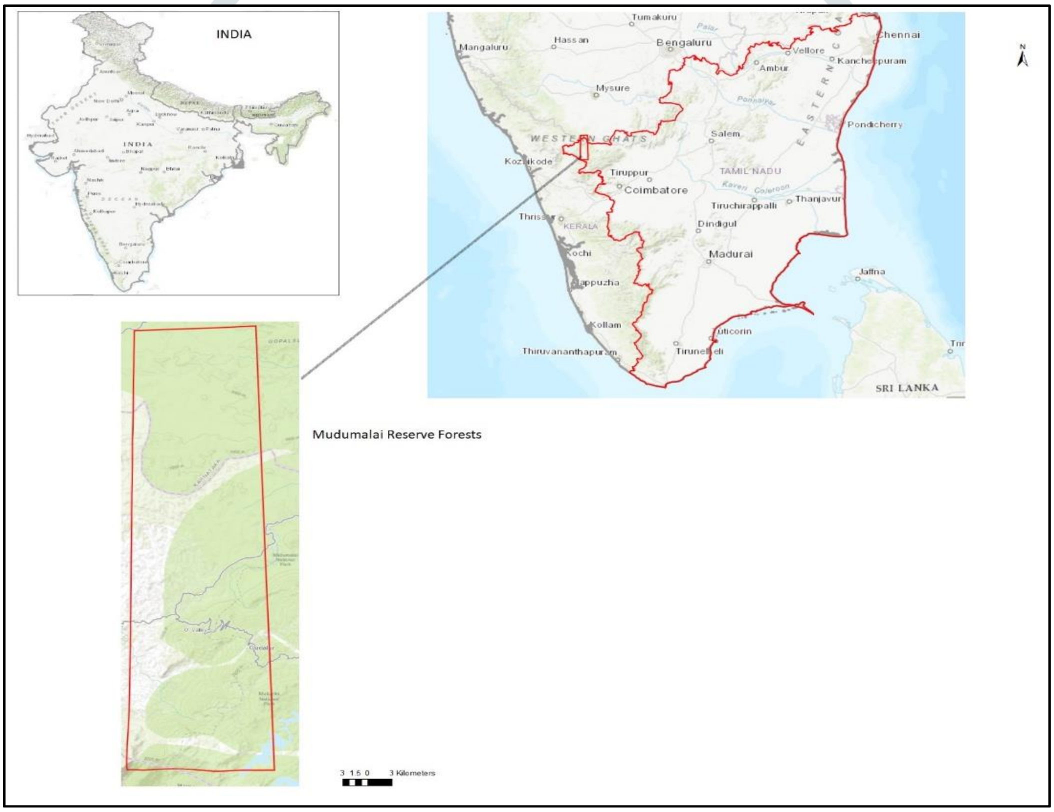

Figure 1: Study Area- Mudumalai Forest.

In Mudumalai forest, June and July is the dry season. Most common trees are Lythraceae, Terminlia, crenulate, Anogessisius Latifolia, Acacia Chundra. Leaf flushing began in January until June (Dalbergia Lartfolia, Elaendendron Glancium, Garanga Pinnata. Some species flushing in May. The canopy trees include Lagerstroemeia microcarpa wt, Terminalia cremilata Roth, Agnogeisius Latifolia,and the understorey vegetation included Kydia Calysna Roxb, Casia Fistula, Themeda cymbaria, Lanatana Camera , Chromolaena odorota, King and Robinson etc. (Suresh et al, 2010). Peaks in leaf flushing before the onset of rain. Leaf flushing and flowering occur simultaneously in majority of species during the peak of dry season (Murali and Sukumar, 1994).

Data sets used for the implementing the methodology includes-

a) Space Borne LiDAR Data

The GLAS data for the year 2003-2009 used in the given study was obtained from the ICESat/GLAS NSIDC website. The data sets were pre-processed by means of ICESat /GLAS NGAT tools for the conversions needed for the extraction of the data and waveform visualisation. The data sets were filtered for the year 2008 by means of the available quality flags for saturation, presence of cloud and validity of elevation. The space borne LiDAR data over Sentinel 2 imagery for Mudumalai forest is shown in the Figure 2.

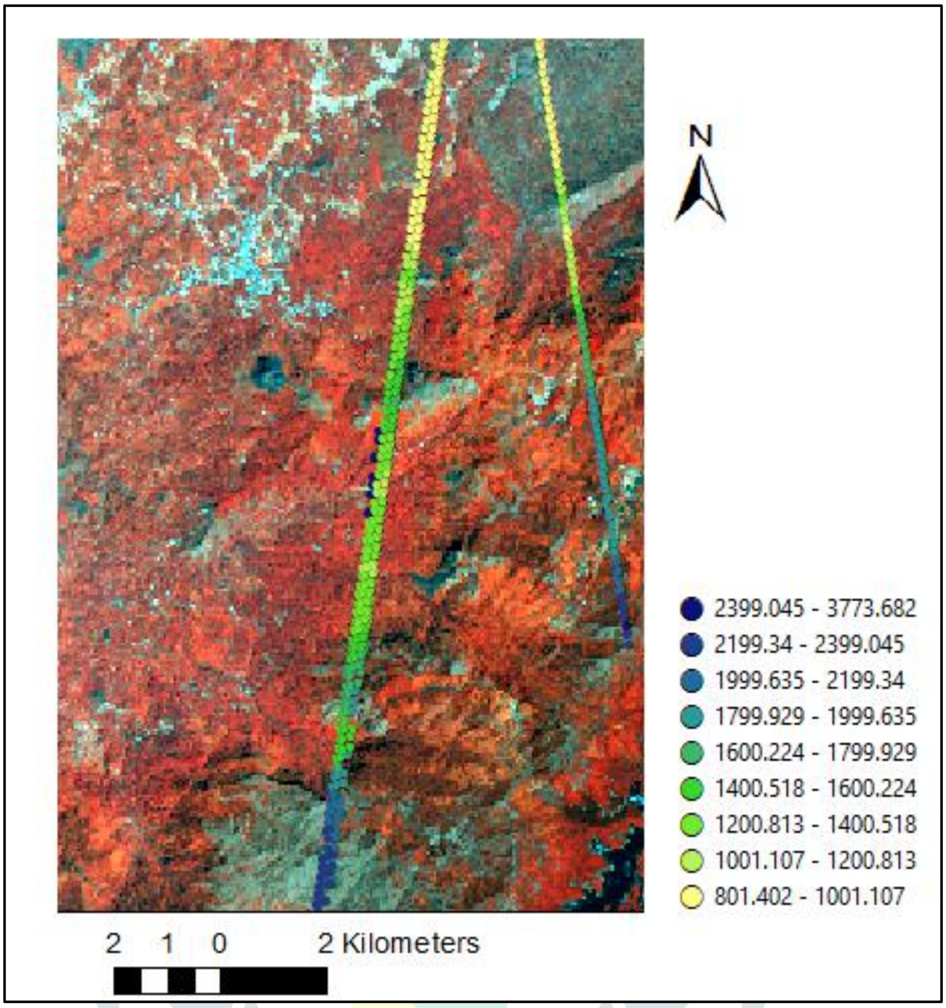

Figure 2: GLAS data coverage which is displayed on Sentinel Data across Mudumalai forest.

b) Sentinel -2 Imagery

Sentinel-2 imagery of 2016 February, March, October and November were downloaded from ESA sentinel-2 USGS Earth explorer (http://eros.usgs.gov/sentinel-2). The Sentinel-2 multispectral instrument (MSI) has 13 spectral bands. Sentinel -2 imagery is pre-processed by means of the SNAP toolbox provided by ESA. Atmospheric and terrain corrections were done by means of ESA toolbox and top of atmospheric reflectance (TOA) were obtained.

3. METHODOLOGY

The methodology of the study is depicted in Figure 3. Structural parameters from GLAS data were obtained by developing digital elevation models and digital surface models.

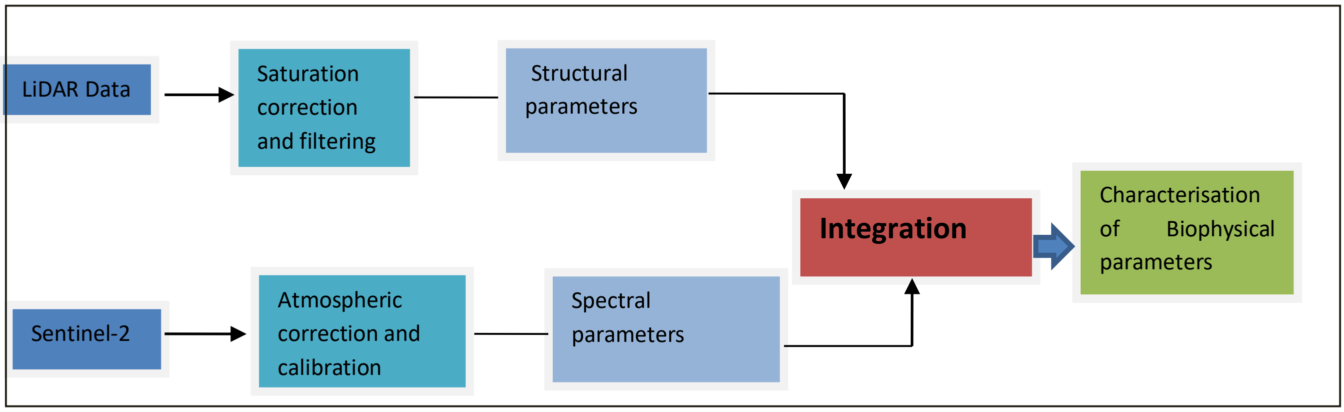

Figure 3: Methodology used in the study

3.1 Estimation of the structural and spectral parameters by integration method

For the Sentinel imagery, pre-processing included the resampling, spatial subset and the cloud removal using SNAP tool. The pre-processed data of sentinel -2 and the structural parameters from LiDAR data were integrated based on pixel-based image registration techniques. NDVI, LAI, FAPAR, F Cover were estimated for the months of October, November, February and March.

3.2 Canopy Height Model (CHM)

From the LiDAR point cloud which is developed from the GLAS space borne data, canopy height models (CHM) of Mudumalai are developed and is given in the Figure 4. CHM were developed for the months of October, November, February and March 2008.

3.3 Normalized Difference vegetation indices (NDVI)

NDVI is most commonly used vegetation indices and is highly correlated with biomass. The values of NDVI range from 0 to 1 and have sensitive response for even low vegetation and calculated through normalisation procedure. NDVI is related to canopy structure and canopy photosynthesis but sensitive to effects of soil brightness, soil colour atmosphere, clouds and leaf canopy shadow. NDVI represents photosynthetic activity and is highly correlated with density of the vegetation. The normalizing reduces topographic and atmospheric effects and enables the simultaneous examination of a wide area. The equation for NDVI is in (1)

$$NDVI=\frac{NIR-RED}{NIR+RED} \qquad (1)$$

3.4 Generation of biophysical variables

From the top of canopy reflectance data, LAI, Forest cover and FAPAR is generated by training the neural networks which is composed of one input layer made of 11 normalized input data, one hidden layer with 5 neurons with tangent sigmoid transfer functions and one output layer with a linear transfer function.

a) Leaf Area Index

Leaf Area Index is defined as the one-sided green leaf area per unit ground area in broadleaf canopies (Breuer et al, 2002).

LAI is estimated by equation (2)

$$LAI= 0.57*\exp(2.33\ NDVI) \qquad (2)$$

b) Forest cover

Forest cover is defined as an area having more than 1ha with tree canopy density of more than 10 percent.

c) Fraction of Absorbed Photosynthetically Active Radiation

It is the fraction of the incoming solar radiation in the photosynthetically active radiation spectral region and it gives information of the light absorption across an integrated plant canopy and is directly related to the primary productivity of photosynthesis and the assimilation of carbon dioxide in vegetation

d) Estimation of Biomass

Support vector machine (SVM) learning algorithm is used in the given study for the estimation of biomass. SVM is a promising machine learning methodology for biomass estimation which uses radial basis kernel function and grid search. Here the CHM from space borne LiDAR point cloud were integrated with the LAI estimated on pixel based fusion strategy. SVM regression is applied on the integrated imagery. Biomass is estimated for the study area for different phenological seasons. The biomass estimated for the study area for the different months is depicted in the Figure 4.

4. RESULTS AND DISCUSSION

Canopy height model of Mudumalai forest were obtained from the GLAS data and is shown in the Figure 4.

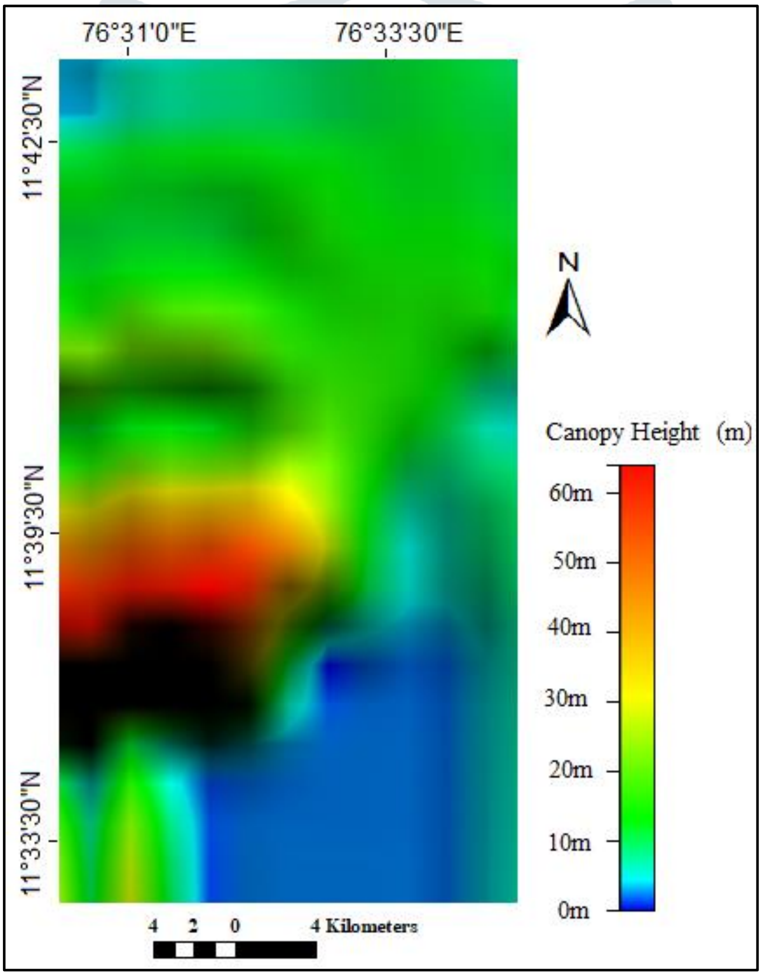

Figure 4: CHM for Mudumalai Forest

Different biophysical parameters estimated and seasonal variation corresponding to different months for the study area are depicted in the Figure 5.

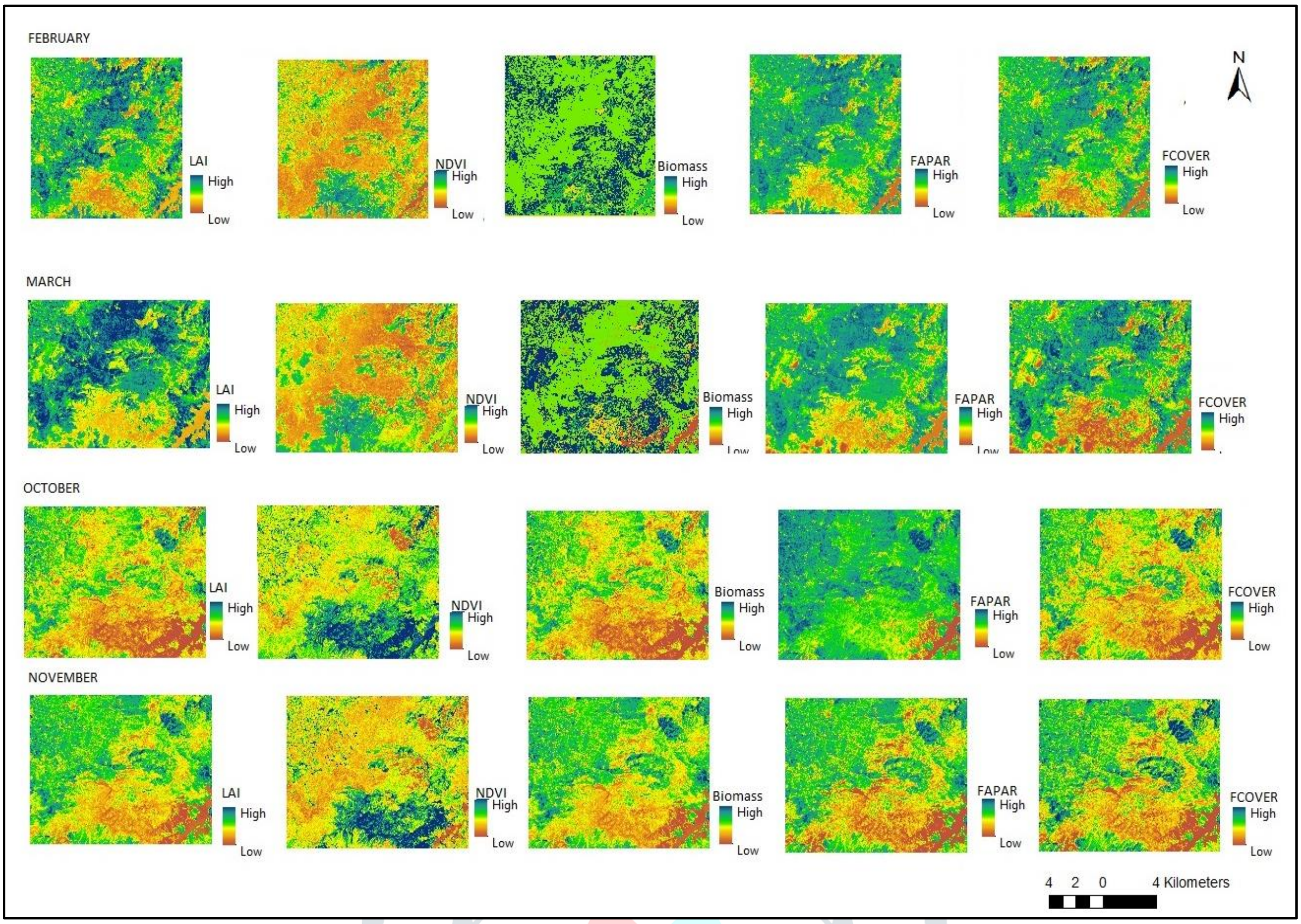

Figure 5: Biophysical variables estimated for Mudumalai Forest

The estimated biomass and LAI were compared with the field measurements, and obtained consistent correlation is obtained. Scatter plot showing the comparison is given in Figure 6. Close correlation of R^2 =0.98, for biomass and R^2=0.982 for LAI is obtained.

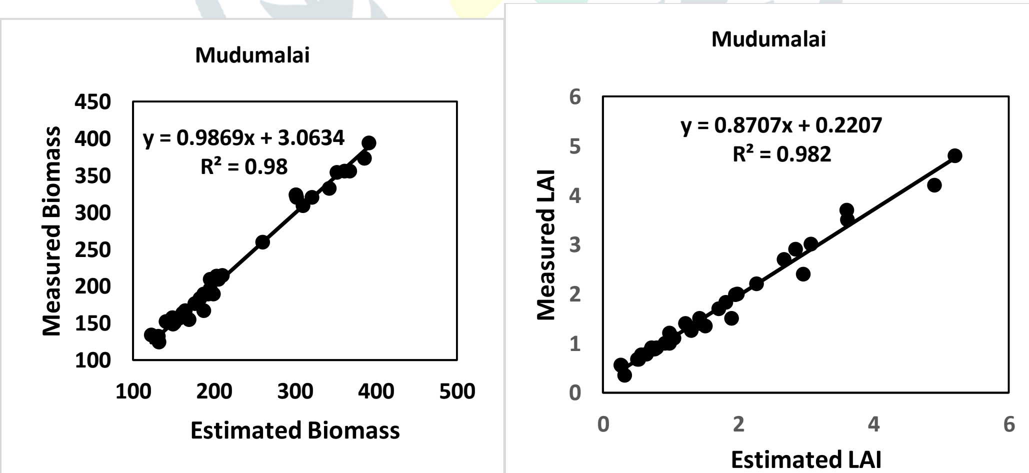

Figure 6: Scatter plot showing the variation of biomass and LAI with ground measurements

The estimated parameters successfully depicted the phenological variations in Mudumalai forests. The results indicated that the integrated product of space borne LiDAR data with Sentinel-2 images can extract real time based biophysical parameters in an effective manner. Biomass are also computed which can be an indirect indicator of the carbon content in the forest area. The integration with the space borne LiDAR point cloud provide the opportunity to extract the structural parameters including canopy heights. Dense time series data of Sentinel enabled to capture the forest phenology on real time basis. A significant correlation is seen between the biomass and the vegetation indices. The paper presented the potential of the combination of GLAS data and Sentinel-2 images for the extraction of biophysical parameters along with the structural parameters and the monitoring forest phenology in a cost effective and accurate way. Spectral parameters were calculated based on the reflectance values of the Sentinel data thus ensuring the quality of the results as well as the ability to identify the forest conditions and the canopy changes.

5. CONCLUSION

The study estimated the biophysical parameters by the integration of space borne LiDAR and Sentinel-2 images in heterogeneous forests. The biophysical parameters estimated are canopy heights, Forest cover, FAPAR, biomass, NDVI and LAI. The study focussed on a cost effective and accurate estimation of the spectral parameters along with the structural parameters by the integration approach. The spectral parameters calculated here were a good indicator of the forest canopy cover, moisture content, vegetation density, biomass and the vegetation growth. The study thus successfully elucidated the phenological variations of Mudumalai forest. The data fusion of the GLAS and the Sentinel-2 images proved to be a promising technology for the forest structural and spectral parameters in addition to the accurate phenological monitoring. The biophysical parameters extracted can give accurate and desirable results which can play a significant role in the national forest monitoring and the forest management practices.

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REFERENCES

1. Andersen, H. E., Reutebuch, S. E., & McGaughey, R. J. (2006). A rigorous assessment of tree height measurements obtained using airborne-LiDAR and conventional field methods. *Canadian Journal of Remote Sensing*, *32*(5), 355-366.
2. Arora, V. K., & Boer, G. J. (2005). A parameterization of leaf phenology for the terrestrial ecosystem component of climate models. *Global Change Biology*, *11*(1), 39-59.
3. Bhat, D. M., & Murali, K. S. (2001). Phenology of understorey species of tropical moist forest of Western Ghats region of Uttara Kannada district in South India. *Current Science*, 799-805.
4. Borchert, R. (1980). Phenology and ecophysiology of tropical trees: Erythrina poeppigiana OF Cook. *Ecology*, *61*(5), 1065-1074.
5. Borchert, R. (1994). Soil and stem water storage determine phenology and distribution of tropical dry forest trees. *Ecology*, *75*(5), 1437-1449.
6. Bullock, S. H., & Solis-Magallanes, J. A. (1990). Phenology of canopy trees of a tropical deciduous forest in Mexico. *Biotropica*, 22-35.
7. Cairns, M. A., Brown, S., Helmer, E. H., & Baumgardner, G. A. (1997). Root biomass allocation in the world's upland forests. *Oecologia*, *111*(1), 1-11.
8. Corlett, R. T., & Lafrankie, J. V. (1998). Potential impacts of climate change on tropical Asian forests through an influence on phenology. *Climatic change*, *39*(2-3), 439-453.
9. Das, S., & Singh, T. P. (2012). Correlation analysis between biomass and spectral vegetation indices of forest ecosystem. *International Journal of Engineering Research and Technology*, *1*(5), 1-13.
10. Dube, T., & Mutanga, O. (2015). Evaluating the utility of the medium-spatial resolution Landsat 8 multispectral sensor in quantifying aboveground biomass in uMgeni catchment, South Africa. *ISPRS Journal of Photogrammetry and Remote Sensing*, *101*, 36-46.
11. Gao, H., Wang, L., Jing, L., & Xu, J. (2016, April). An effective modified water extraction method for Landsat-8 OLI imagery of mountainous plateau regions. In *IOP Conference Series: Earth and Environmental Science* (Vol. 34, No. 1, p. 012010). IOP Publishing.
12. Hajj, M. E., Baghdadi, N., Fayad, I., Vieilledent, G., Bailly, J. S., & Minh, D. H. T. (2017). Interest of integrating spaceborneLiDAR data to improve the estimation of biomass in high biomass forested areas. *Remote Sensing*, *9*(3), 213.
13. Hall, F. G., Shimabukuro, Y. E., & Huemmrich, K. F. (1995). Remote sensing of forest biophysical structure using mixture decomposition and geometric reflectance models. *Ecological applications*, *5*(4), 993-1013.
14. Hudak, A. T., Strand, E. K., Vierling, L. A., Byrne, J. C., Eitel, J. U., Martinuzzi, S., & Falkowski, M. J. (2012). Quantifying aboveground forest carbon pools and fluxes from repeat LiDAR surveys. *Remote Sensing of Environment*, *123*, 25-40.
15. Hufkens, K., Friedl, M., Sonnentag, O., Braswell, B. H., Milliman, T., & Richardson, A. D. (2012). Linking near-surface and satellite remote sensing measurements of deciduous broadleaf forest phenology. *Remote Sensing of Environment*, *117*, 307-321.
16. Janzen, D. H. (1978). Seeding patterns of tropical trees. *Tropical trees as living systems*, 83-128.
17. Karlson, M., Ostwald, M., Reese, H., Sanou, J., Tankoano, B., & Mattsson, E. (2015). Mapping tree canopy cover and aboveground biomass in Sudano-Sahelian woodlands using Landsat 8 and random forest. *Remote Sensing*, 7(8), 10017-10041.
18. Laurance, W. F. (2004). Forest-climate interactions in fragmented tropical landscapes. *Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences*, *359*(1443), 345-352.
19. Lee, S., Ni-Meister, W., Yang, W., & Chen, Q. (2011). Physically based vertical vegetation structure retrieval from ICESat data: Validation using LVIS in White Mountain National Forest, New Hampshire, USA. *Remote Sensing of Environment*, *115*(11), 2776-2785.
20. Lefsky, M. A. (2010). A global forest canopy height map from the Moderate Resolution Imaging Spectroradiometer and the Geoscience Laser Altimeter System. *Geophysical Research Letters*, *37*(15).

21. Lefsky, M. A., Cohen, W. B., Acker, S. A., Parker, G. G., Spies, T. A., & Harding, D. (1999). Lidar remote sensing of the canopy structure and biophysical properties of Douglas-fir western hemlock forests. *Remote sensing of environment*, *70*(3), 339-361.
22. Lefsky, M. A., Cohen, W. B., Acker, S. A., Spies, T. A., Parker, G. G., & Harding, D. (1998, July). Lidar remote sensing of forest canopy structure and related biophysical parameters at HJ Andrews experimental forest, Oregon, USA. In *Geoscience and Remote Sensing Symposium Proceedings, 1998. IGARSS'98. 1998 IEEE International* (Vol. 3, pp. 1252-1254). IEEE.
23. Lieth, H. (1974). Purposes of a phenology book. In *Phenology and seasonality modeling* (pp. 3-19). Springer, Berlin, Heidelberg.
24. Liu, W., & Chen, Q. (2013). Synergistic use of satellite laser altimetry and shuttle radar topography mission DEM for estimating ground elevation over mountainous vegetated areas. *IEEE Geoscience and Remote Sensing Letters*, *10*(3), 481-485.
25. Lu, D., Mausel, P., Brondizio, E., & Moran, E. (2004). Change detection techniques. *International journal of remote sensing*, *25*(12), 2365-2401.
26. Luo, S., Wang, C., Li, G., & Xi, X. (2013). Retrieving leaf area index using ICESat/GLAS full-waveform data. *Remote sensing letters*, *4*(8), 745-753.
27. Maherali, H., Pockman, W. T., & Jackson, R. B. (2004). Adaptive variation in the vulnerability of woody plants to xylem cavitation. *Ecology*, *85*(8), 2184-2199.
28. Mahoney, C., Hopkinson, C., Held, A., Kljun, N., & Van Gorsel, E. (2016). ICESat/GLAS Canopy Height Sensitivity Inferred from Airborne Lidar. *Photogrammetric Engineering & Remote Sensing*, *82*(5), 351-363.
29. Menzel, A. (2002). Phenology: its importance to the global change community. *Climatic change*, *54*(4), 379-385.
30. Moore, C. E., Brown, T., Keenan, T. F., Duursma, R. A., Van Dijk, A., Beringer, J., ... & Maier, S. (2016). Reviews and syntheses: Australian vegetation phenology: new insights from satellite remote sensing and digital repeat photography.
31. Murali, K. S., & Sukumar, R. (1993). Leaf flushing phenology and herbivory in a tropical dry deciduous forest, southern India. *Oecologia*, *94*(1), 114-119.
32. Murali, K. S., & Sukumar, R. (1994). Reproductive phenology of a tropical dry forest in Mudumalai, southern India. *Ecology*, *82*, 759-767.
33. Newstrom, L. E., Frankie, G. W., & Baker, H. G. (1994). A new classification for plant phenology based on flowering patterns in lowland tropical rain forest trees at La Selva, Costa Rica. *Biotropica*, 141-159.
34. Parihar, J. S., Goroshi, S., Singh, R. P., Krishnayya, N. S. R., Sirsayya, M. B., Kumar, A., ... & Sonakia, A. (2013). Observation of forest phenology using field-based digital photography and satellite data. *Current Science*, 1740-1747.
35. Pesaresi, M., Corbane, C., Julea, A., Florczyk, A., Syrris, V., & Soille, P. (2016). Assessment of the added-value of Sentinel-2 for detecting built-up areas. *Remote Sensing*, *8*(4), 299.
36. Popescu, S. C., Wynne, R. H., & Nelson, R. F. (2003). Measuring individual tree crown diameter with lidar and assessing its influence on estimating forest volume and biomass. *Canadian journal of remote sensing*, *29*(5), 564-577.
37. Reed, B. C., Brown, J. F., VanderZee, D., Loveland, T. R., Merchant, J. W., & Ohlen, D. O. (1994). Measuring phenological variability from satellite imagery. *Journal of vegetation science*, *5*(5), 703-714.
38. Reich, P. B. (1995). Phenology of tropical forests: patterns, causes, and consequences. *Canadian Journal of Botany*, *73*(2), 164-174.
39. Reich, P. B., & Borchert, R. (1984). to Journal of Ecology. *Journal of Ecology*, *72*(1), 61-74.
40. Sakai, S. (2001). Phenological diversity in tropical forests. *Population Ecology*, *43*(1), 77-86.
41. Schutz, B. E., Zwally, H. J., Shuman, C. A., Hancock, D., & DiMarzio, J. P. (2005). Overview of the ICESat mission. *Geophysical Research Letters*, *32*(21).
42. Shukla, R. P., & Ramakrishnan, P. S. (1982). Phenology of trees in a sub-tropical humid forest in north-eastern India. *Vegetatio*, *49*(2), 103-109.
43. Singh, J. S., & Singh, V. K. (1992). Phenology of seasonally dry tropical forest. *CURRENT SCIENCE-BANGALORE-*, *63*, 684-684.
44. Sundarapandian, S. M., Chandrasekaran, S., & Swamy, P. S. (2005). Phenological behaviour of selected tree species in tropical forests at Kodayar in the Western Ghats, Tamil Nadu, India. *Current Science*, *88*(5), 805-810.
45. Suresh, H. S., Dattaraja, H. S., & Sukumar, R. (2010). Relationship between annual rainfall and tree mortality in a tropical dry forest: results of a 19-year study at Mudumalai, southern India. *Forest Ecology and Management*, *259*(4), 762-769.
46. Tan, K., Piao, S., Peng, C., & Fang, J. (2007). Satellite-based estimation of biomass carbon stocks for northeast China's forests between 1982 and 1999. *Forest ecology and management*, *240*(1-3), 114-121.
47. Tang, H., Brolly, M., Zhao, F., Strahler, A. H., Schaaf, C. L., Ganguly, S., ... & Dubayah, R. (2014). Deriving and validating Leaf Area Index (LAI) at multiple spatial scales through lidar remote sensing: A case study in Sierra National Forest, CA. *Remote Sensing of Environment*, *143*, 131-141.
48. van Schaik, C. P., Terborgh, J. W., & Wright, S. J. (1993). The phenology of tropical forests: adaptive significance and consequences for primary consumers. *Annual Review of ecology and Systematics*, *24*(1), 353-377.
49. Veloso, A., Mermoz, S., Bouvet, A., Le Toan, T., Planells, M., Dejoux, J. F., & Ceschia, E. (2017). Understanding the temporal behavior of crops using Sentinel-1 and Sentinel-2-like data for agricultural applications. *Remote sensing of environment*, *199*, 415-426.
50. Vrieling, A., de Beurs, K. M., & Brown, M. E. (2011). Variability of African farming systems from phenological analysis of NDVI time series. *Climatic change*, *109*(3-4), 455-477.
51. Vrieling, A., Skidmore, A. K., Wang, T., Meroni, M., Ens, B. J., Oosterbeek, K., ... & Paganini, M. (2017). Spatially detailed retrievals of spring phenology from single-season high-resolution image time series. *International journal of applied earth observation and geoinformation*, *59*, 19-30.

52. Wang, D., Xin, X., Shao, Q., Brolly, M., Zhu, Z., & Chen, J. (2017). Modeling Aboveground Biomass in Hulunber Grassland Ecosystem by Using Unmanned Aerial Vehicle Discrete Lidar. *Sensors*, *17*(1), 180.
53. Wang, Y., Li, G., Ding, J., Guo, Z., Tang, S., Wang, C., ... & Chen, J. M. (2016). A combined GLAS and MODIS estimation of the global distribution of mean forest canopy height. *Remote Sensing of Environment*, *174*, 24-43.
54. Wulder, M. A., Bater, C. W., Coops, N. C., Hilker, T., & White, J. C. (2008). The role of LiDAR in sustainable forest management. *The Forestry Chronicle*, *84*(6), 807-826.
55. Zhang, X., Friedl, M. A., Schaaf, C. B., Strahler, A. H., Hodges, J. C., Gao, F., ... & Huete, A. (2003). Monitoring vegetation phenology using MODIS. *Remote sensing of environment*, *84*(3), 471-475.
56. Zwally, H. J., Schutz, B., Abdalati, W., Abshire, J., Bentley, C., Brenner, A., ... & Herring, T. (2002). ICESat's laser measurements of polar ice, atmosphere, ocean, and land. *Journal of Geodynamics*, *34*(3), 405-445.