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Accounting Forest Carbon Sequestration Using Integrated Geospatial Techniques

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Abstract

Forest aboveground biomass (AGB) serves as a vital ingredient for global climate change policy making. It serves as an indicator of climate change in term of carbon sequestered in forests and act as a key constituent in the carbon cycle that moderates the global climate. Hence, monitoring the carbon dynamics becomes extremely important in terms of ecological services. Remote Sensing is an advanced tool for suitable and accurate measurements of forest AGB on a regional scale. The study targets in the assessment of forest AGB over the mixed deciduous tropical forests of Bhimbandh Wildlife Sanctuary in Bihar (India) using forest-based inventory and integrated geospatial approaches to develop a regression model based on the statistical correlation between AGB measured at plot level and the associated spectral parameters derived from IRS P-6 LISS III sensor. AGB map is generated from the best-fit model in GIS platform following the top-down and bottom-up inventory approach, which is further converted to carbon map using standard carbon conversion factor. The methodology adopted helped in developing a robust yet simple approach in proper accounting of forest sequestered carbon in terms of AGB using integrated geospatial techniques. Hence, the study recommends the combined use of information generated from both the field-based forest inventory and geospatial approaches for better assessment of stand biomass with significant contribution towards operational forestry and climate change studies, in context to REDD (Reduced Emissions from Deforestation and forest Degradation)/REDD+ regimes for measuring and monitoring the current state and dynamics of forest carbon stocks.

Introduction

The burning issue of Climate Change and the related concept of REDD (Reducing Emissions from Deforestation and forest Degradation) is gaining momentum in climate change policy negotiations at global and national levels. The United Nations Framework Convention on Climate Change (UNFCCC) adopted this concept of REDD in order to provide fiscal incentives for reductions in emissions from deforestation below a critical level in the developing countries. Development of this concept is briefed out by Sharma et al. 2013). The basic steps involved in the methodology for proper execution of a functional REDD system includes proper evaluation of forest carbon stock dynamics, accounting CO_2 emissions from anthropogenic activities, determining a reference for forest carbon stock dynamics and mobilizing benefits to the local contributors (Sharma et al., 2013).

Measurement of biophysical indicators of forest carbon storage, e.g. tree canopy height or above ground biomass (AGB) is a key parameter to understand the terrestrial carbon balance (Santoro and Kellndorfer, 2012). Also, accurate estimate of biomass, viz. the carbon content of forests is a critical information for REDD. Forest biomass can be assessed either through field-based measurements or by remotely sensed methods (Sinha et al., 2015a). Forest biomass is an important component for studying the carbon cycle dynamics and is one of key indicators of climate change and forest health (Sinha et al., 2014; 2018). Biomass varies with land cover types and an improved classification is important in this case (Sinha et al., 2015c). Some recent studies using vegetation indices generated from optical satellite data have shown good results for assessing biomass (Kumar et al., 2013). However, several studies using optical remote sensing data showed poor or moderately low correlation values for biomass estimation, which is observed mostly ≤ 0.3 (Hyyppa et al., 2000; Foody et al., 2003; Thenkabail et al., 2004; Sinha et al., 2016). Some studies, however, documented an increase in the correlation using exponential transformation of the variables in regression. Regression analysis is not considered an effective technique for estimating forest parameters from digital satellite imagery data by several, since correlation of determination, a measure of precision used in regression modeling, is hardly capable of explaining more than even 50 % variation by the methods (Rahman et al., 2008). However, regression analysis has been observed a good option for biomass estimation using Landsat generated vegetation indices (Zheng et al., 2017).

Microwave SAR data has the potential to give better predictions for biomass estimation, mainly for low biomass than high biomass and retrieval of other forest parameters than the optical remote sensing data, even during adverse climatic conditions and diurnal variations (Sinha, 2015a). Simultaneous use of optical and SAR can enhance this limit and improve the biomass assessment (Sinha et al., 2016). The use of integrated multi-frequency SAR provides even better alternative for biomass estimation (Sinha et al., 2017). The synergic use of optical and multi-frequency SAR can enhance the accuracy of the estimation even further (Sinha, 2017). Studies shows the development of qualitative evaluation of vegetation parameters work better with polarimetric complex SAR data (Maity et al., 2011), however, Sinha (2016) showed poor relationship between biomass and Polarimetric Scattering Parameter products. SAR interferometry also adds valuable information regarding forest biomass ((Sinha et al., 2015b; Kumar, 2009).

Materials and Methods

Study area and datasets: A case study of mixed deciduous tropical forest of Bhimbandh Wildlife Sanctuary, Bihar in India with geographic extent of 25º19'30"N - 24º56'50"N latitudes and 86º33'33"E - 86º11'51"E is considered for the study and represented in Figure 1. Details of the study area are mentioned in literatures (Sinha et al., 2013; Sinha and Sharma, 2013). Data from optical satellite sensor of IRS P-6 LISS III of 2012 with a spatial resolution of 23.5 m is used in this study.

Field inventory: It is generated from in-situ field data collection of certain dendrometric parameters like stand height and girth at breast height (GBH), along with the species type, density and composition through random sampling approach during 2012. 34 square sample plots of 0.1 hectare area are selected over the entire area that represents the variability and homogeneous vegetation units of the forest area. GBH was converted to DBH (Diameter at Breast Height) and using this information along with tree height information, the tree volumes were estimated via volumetric equations and biomass were calculated after multiplying each tree volume with the respective specific gravity (Sinha et al., 2016, 2018).

IRS P-6 LISS III image transformation

The LISS-III imagery is geometrically rectified and co-registered to the Survey of India (SOI) toposheet considering analogous distinct identifiable objects on the toposheets, ground and image (Sinha et al., 2013). Principal components, texture measures and NDVI were calculated from the image. NDVI showed the strongest relationship with the biomass among all the vegetation indices (Kumar et al., 2013). Sarker (2010) highlighted the importance of texture measures in biomass assessment. Texture analysis with 3×3 floating window size for individual LISS-III bands were performed using occurrence matrices. Concurrently, texture measures of the principal components were also analyzed using the same window size.

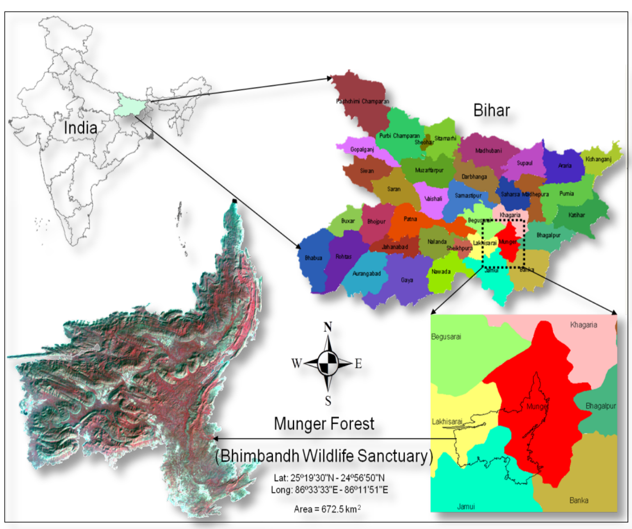

Figure 1. Location map of the study area.

Biomass/carbon MLR modelling

Metrices derived from LISS-III image were equated to the field-based plot biomass. Multiple Linear Regression (MLR) analysis was used to integrate the metrices statistically to obtain the best fit model that enhanced the model estimate accuracy. The performance of the model was judged on the basis of coefficient of determination (R^2) values between estimated and predicted biomass and the RMSE (root mean square error) of the estimates. The model was then validated with nine additional field biomass data of year 2015 and the validation was accounted based on the aforesaid statistical measures, along with a non-dimensional statistical measure, namely Willmott's index of agreement (d).

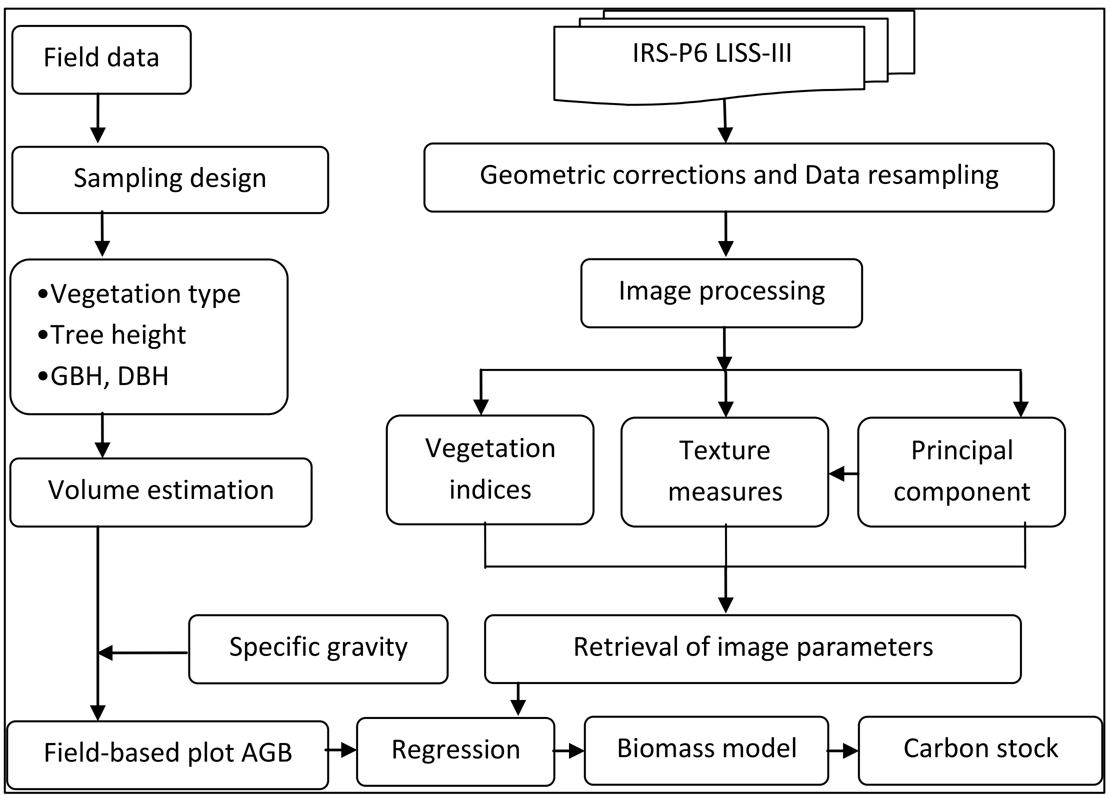

Figure 2. Approach of the study.

After validating, the biomass model was transformed to derive carbon stock values using conversion factors of 0.5 and then to carbon dioxide by multiplying with 3.67 (Mushtaq and Malik, 2014; Rashid et al., 2017; Waikhom et al., 2017). The resultant model was finally represented spatially in the form of forest carbon sequestration map in GIS framework. The entire flow-diagram of the methodology adopted in the study is represented in Figure 2.

Results and Discussion

The biomass model: On regressing, the NDVI values to the plot AGB, a maximum R^2 value of 0.26 was obtained following linear model as the best fit. Equation 1describes the relation between NDVI and field-based biomass which is further used as an ingredient in the final synergic model for biomass prediction.

$$Biomass = 340.1 * NDVI - 143.1 \quad \text{(Eq. 1)}$$

Among the texture metrices, the highest R^2 value was obtained for the variance of Near Infra-red (NIR) band of LISS-III imagery in a logarithmic model. Equation 2 defines the relation between NIR band variance and field-based biomass which again is further used as an input for the final synergic model for biomass prediction.

$$Biomass = 81.8 * e^{(-0.0562 * NIR_{variance})} \quad \text{(Eq. 2)}$$

PCA and texture measures of PCA components were simultaneously analyzed. The greatest correlation of plot biomass was observed with the first principal component (PCA1) variance in logarithmic model. Equation 3 shows the relation between PCA1 variance and field-based biomass which again is further used as an input for the final synergic model for biomass prediction.

$$Biomass = 76.8 * e^{(-0.003 * PCA1_{variance})} \quad \text{(Eq. 3)}$$

Multiple Linear Regression (MLR) analysis was performed and the Equations 1, 2 and 3 were statistically combined to design the best fit integrated model and represented as Equation 4. The same equation represents the biomass prediction model generated from optical satellite data.

$$\begin{aligned} Biomass &= 289.1 * NDVI + 54.2 * e^{(-0.0562 * NIR_{variance})} \\ &- 20.6 * e^{(-0.003 * PCA1_{variance})} - 136.3 \end{aligned} \quad \text{(Eq. 4)}$$

Model performance and validation statistics

Performance of the best-fit model (A) as described in Equation 4 is signified by the following statistics mentioned in Table 1, in terms of R^2, RMSE and average absolute accuracy. A correlation of 0.3 is observed between the observed and estimated biomass, with RMSE of 35 Mg/ha and a model accuracy of 47.5%. On validation of the model (B), a moderately high correlation value of 0.6 is obtained between the observed and estimated biomass, and the Willmott's Index of agreement of 0.72 between the modelled and the actual field data.

Table 1: Model evaluation (A) and validation (B) parameters for biomass prediction.

	R^2	RMSE (Mg/ha)	Average Absolute Accuracy	Willmott's Index (*d*)
A	0.3	35	47.5%	-
B	0.6	26.7	-	0.72

Biomass/carbon maps: Spatial information

Figure three illustrates the forest above-ground biomass map of the study site using Equation 4 and is categorized into ten classes based on biomass levels from very low (<25 Mg/ha and 25-50 Mg/ha), low (50-75 Mg/ha and 75-100 Mg/ha), moderate (100-125 Mg/ha and 125-150 Mg/ha), high (150-175 Mg/ha and 175-200 Mg/ha) to very high (>250 Mg/ha). Maximum proportion of the biomass lies with 125 Mg/ha and average biomass of the area is calculated to 41.33 Mg/ha. The forest carbon stock and carbon dioxide map is portrayed in Figure 4 that demonstrates the spatial information of carbon over the entire area. The map is simultaneously reclassified into five classes according to the concentration levels as depicted in the Figure 4. Most of the forested area lies within the carbon stock concentration of 25-75 CMg/ha. The total biomass and carbon stock over the entire study area is calculated to 2779442.5 and 1389721.25 Mg respectively.

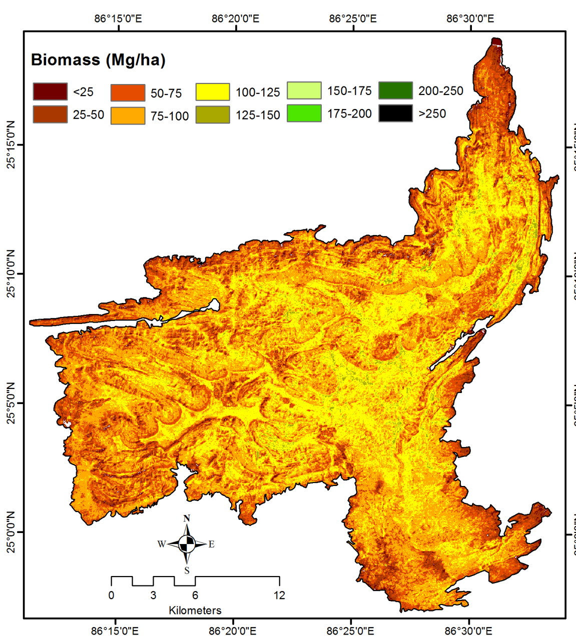

Figure 3. Spatial forest above-ground biomass map.

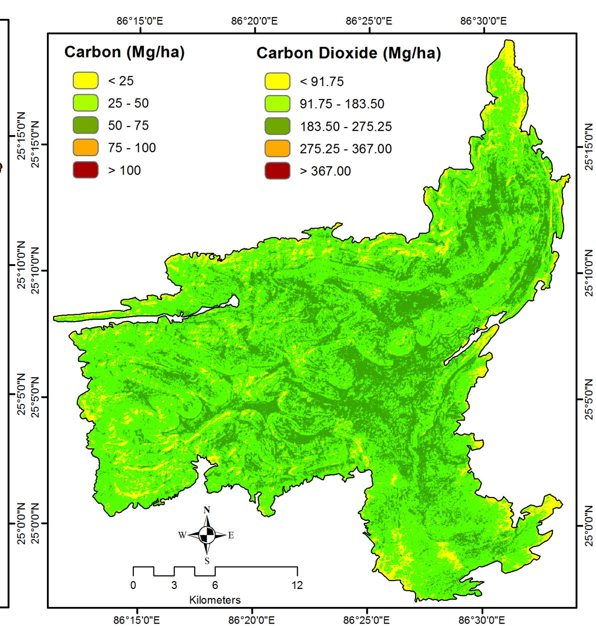

Figure 4. Spatial forest carbon stock and carbon dioxide concentration map.

Conclusion

The approach in the study exposes the prospects of LISS-III data for modelling and mapping above ground forest biomass and carbon over mixed deciduous tropical forests. Results indicate that the NIR band in the visible spectrum of LISS-III delivers the utmost information on forest biomass. Results also signify the contribution of textural measures and principal components along with NDVI in the estimation of biomass with optical sensor. The accuracy in the estimation shall vary with the number and mode of sampling, climatic parameters, sensors used, models and algorithms adopted in the study, etc. Limitations of the study were the biasness in selecting the sample plots, although the plots were selected in such a way so that they represent all the vegetation strata found in the area. The other constraints being the complexity of forest stand structure, and non-transferable of the model to different areas; however, the approach can be universally adopted. The application of LiDAR, hyperspectral and microwave remote sensing can enhance the accuracy of the estimates; however, the ease in accessibility of the optical data provides an upper hand. What-so-ever, irrespective of the sensor, remote sensing technology provides a faster, cost effective, easier and timely measurement with moderate to high accuracy.

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Authors Contribution: *Suman Sinha (Post-Doctoral Fellow) is responsible for performing the research work; data collection. He is writing, editing and corresponding author of manuscript.*

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