

Predictive Analysis for Vegetation Biomass Assessment in Western Ghat Region (WG) Using Geospatial Techniques

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Abstract Forests play a critical role in ecological functioning, global warming and climate change through its unique potential to capture and hold carbon (C). Biomass is one of the indicator of the status of forests hence accurate assessment and biomass mapping is important for sustainable forest management. The objectives of this study is to estimate above ground biomass (AGB) from field inventory data and to map AGB combining field inventory data, remote sensing and geostatistical model. In the present study stratified random sampling were used for estimation of biomass in which 59 plots were laid down in different homogenous strata depending on the NDVI values for the region of Maharashtra Western Ghats. The above ground biomass from field ranged from 0.05 to 271 t-dry wt ha⁻¹ in which trees added maximum towards total biomass followed by shrubs and herbs. This paper evaluates the best vegetation indices to estimate biomass. This study was carried out by using Landsat TM satellite data and field inventory data in the Ratnagiri district of Maharashtra, India. A significant correlation was observed between biomass and vegetation indices. The best fit regression equation developed from field above ground biomass and NDVI with R² value of 0.61 was used for spectral modeling to estimate the geospatial distribution of AGB in the entire region. The results of spatial predictions Geostatistical technique and remotely sensed data as auxiliary variables were compared using statistical error methods. This study employed Mean error, Root-Mean-Square error, Average Standard error and Root-Mean Square Standardized error. The ME, RMSE, Average Standard error and Root-

Mean Square Standardized error was 0.078, 8.032, 7.982 and 0.967 respectively. The results showed that cokriging technique is one of the geostatistical method for spatial predictions of biomass in the studied region. The present study revealed that remote sensing technique combined with field sampling provides quick and reliable estimates of above ground biomass and carbon pool and can be used as baseline information for further temporal studies of biomass status of the region and in planning of forest and natural resources management.

Keywords Biomass · Geostatistics · Co-kriging · Remote sensing · Western Ghat

Introduction

Forests are crucial for ecological functions, by regulating the climate because it offers a significant potential to capture and hold carbon (C). Forest biomass accounts for the largest terrestrial carbon pool (Zhao and Zhou 2005; Tan, et al. 2007; Kumar et al. 2011; Borah et al. 2013). When forests are cleared or degraded by anthropogenic actions and natural disturbances a large amount of carbon is released into the atmosphere (Gibbs et al. 2007). The growing concentration of Carbon dioxide (CO₂) and other greenhouse gases have raised concerns of global warming and climatic changes (Thakur and Swamy 2010). Forest covers nearly one-third of the total global land area and store a vast amount (289 Gt) of atmospheric carbon in their biomass alone (FAO 2010). Recently, the estimation of forest biomass has received considerable interest for both practical forestry issues and scientific purposes (Tan et al. 2007; Srinath 2008; Akhavan and Kia-Daliri 2010; Devagiri et al. 2013). The Kyoto Protocol to the United Nations Framework Convention on Climate Change (UNFCCC) has recognized terrestrial

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vegetation as significant sinks of atmospheric carbon dioxide (USAID, 2009). The UNFCCC introduced “Reducing Emissions from Deforestation and Forest Degradation” (REDD 2009) mechanism which is used to create a financial opportunity for developing countries for the carbon stored in forests in the interest of reducing carbon emissions and sustainable forest management (Cerbu et al. 2011). All the greenhouse gas inventories and emissions reduction programs require reliable, accurate, cost-effective and scientifically robust methods for measurement and monitoring of forest carbon storage (ANSAB 2010; Mohanraj et al. 2011). Therefore, it is crucial to precisely estimate the aboveground forest biomass/carbon in quantifying carbon stocks and fluxes.

There are different methods available to measure AGB but forest inventories and remote sensing (RS) are the two principal data sources which are widely used to estimate AGB (Krankina et al. 2004). The estimations of above-ground biomass (AGB) of forested areas are essential to address various questions like estimations of forest productivity (Chirici et al. 2007; Palmer et al. 2009), to determine the global carbon balance (Hese et al. 2005; Devi and Yadava 2009;) or studying the impacts of forest fires or other disturbances (García-Martín et al. 2008). The traditional techniques based on field measurements are the most accurate for biomass estimation which consist in the implementation of forest inventories where a statistical sampling design is established to acquire data from stand level management inventories (Tiwari and Singh 1984; Srinath 2008; Devi and Yadava 2009; McRoberts et al. 2010), however is not a practical approach because it is extremely costly, destructive sampling of trees, time consuming and labour intensive (Brown 2002). Many previous studies (Foody et al. 2003; Lu 2005; Maynard et al. 2007; Dadhwal et al. 2009; Kale et al. 2009; Thakur and Swamy 2010; Mohanraj et al. 2011; Kumar et al. 2011; Devagiri et al. 2013) have shown that satellite spectral information (spectral band, band ratios, band transformations, etc.) have good correlation with forest biomass and when combined with field measurements, can be used for the estimations of above ground biomass (AGB).

In recent years, many studies have been conducted using geostatistical approaches to predict continuous forest variables (e.g. basal area, density, LAI, tree height, standing volume, above-ground biomass, productivity, etc.) using remote sensing data (Berterretche et al. 2005; Sales et al. 2007; Meng et al. 2009; Akhavan and Kia-Daliri 2010). Geostatistical techniques have become popular tools and are widely used in several studies for modeling spatial structure of ecological data (Burrough 1986; Nanos et al. 2004; Berterretche et al. 2005; Maselli and Chiesi 2006; Akhavan and Kia-Daliri 2010). Co-kriging (CoK) is used to improve spatial predictions of forest biomass by integrating GPS, ground inventory data, remote sensing, and GIS.

Study Area

Ratnagiri is a coastal district of Maharashtra state lying between 15°40' and 18° 5' north latitude, and 73° 5' and 73° 55' east longitude shown in Fig. 1. Ratnagiri is surrounded by Satara, Sangli and Kolhapur districts in the east, Raigad district in the north, the Arabian Sea in the west and Sindhudurg district in the south. It has a geographical area of 8,208 Km². The annual average precipitation is 3,188 mm with few months of very high rainfall. The maximum temperature rarely goes beyond 38 °C in the coast to 40 °C in the interiors. The forests of this district fall into two distinct types tropical moist deciduous forests and sub-tropical evergreen forests. It has a forest area of 64 Sq.km. The chief tree species occurring in this region are Bibba (*Semecarpus anacardium*), kinjal (*Terminalia paniculata*), Kokam (*Garcinia indica*), Amba (*Mangifera Indica*), Ain (*Terminalia tomentosa*), Apta (*Bauhinia racemosa*), Umbar (*Ficus racemosa*), Kusumb (*Schleichera oleosa*), Kumbha (*Careya arborea*), Asana (*Bridelia retusa*), Anjani (*Memecylon edule*), Atak (*Flacourtia Montana*), Jambhul (*Syzigium cumini*), Nilgiri (*Eucalyptus globules*), Suru (*Casuarina equisetifolia*) and Supari (*Areca catechu*).

Materials and Methods

Field Data

In the present study stratified random sampling were used for estimation of biomass in which 59 plots were laid down in different homogenous strata depending on the NDVI values provided by National Remote Sensing Center (NRSC). In the present study, it was envisaged to do sampling of 0.01 % of the area, keeping in view of the time, money and availability of other resources. This sampling strategy resulted into laying out of 59 plots randomly probability proportion to size (PPS) distributed in different homogenous strata depending on the accessibility of location. The size of quadrant was determined based on species area curve (Fig. 2) where the number of species became constant for sample plot size of 30×30 m. The plots geographical locations were recorded by using Global positioning systems (GPS) and Survey of India topo-sheets (47 F, 47 G and 47 H) and structured in a geographic information system (GIS) database. The sample plot size is set to 30×30 m for trees, a 5×5 m subplot is nested to gather information on shrubs and a 1×1 m subplot for herbaceous species as shown in Fig. 3. The diameter at breast height (DBH) of all trees of ≥10 cm DBH and height of all trees in the plot were measured with help of tapes and hypsometer respectively. The forest stand parameters such as Diameter at Breast Height (DBH) and height were used for volume estimation by applying volume equations. The volumetric

Location map of study area

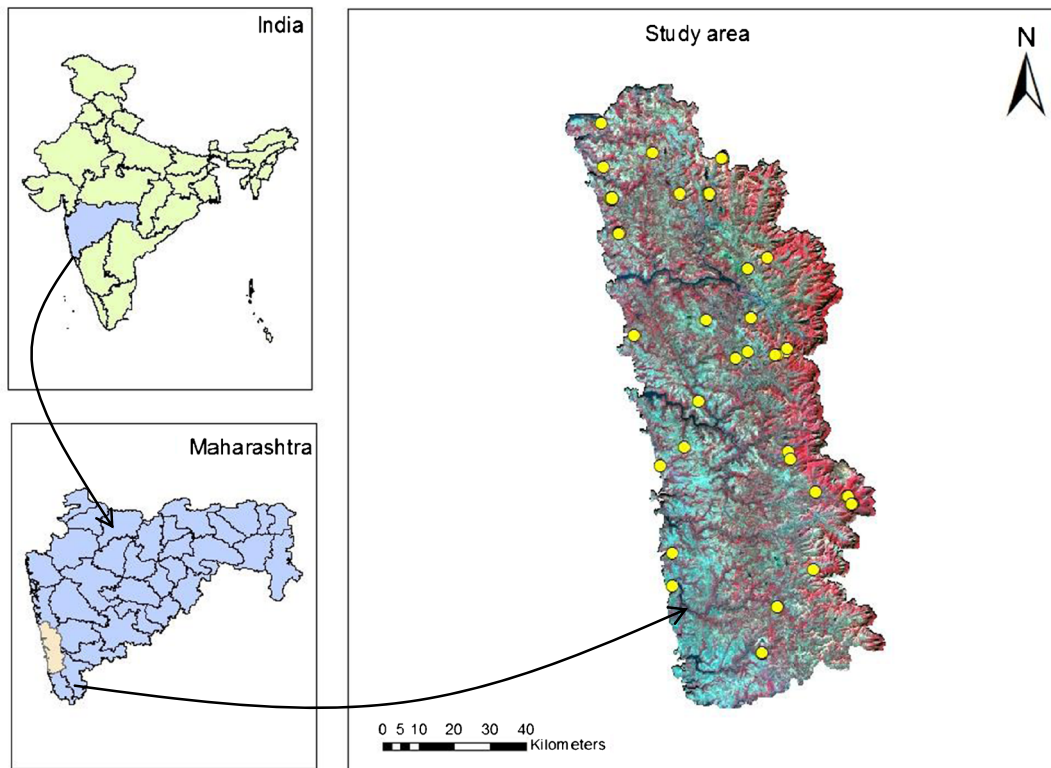


Fig 1 Location map of study area with sampling points

equations developed by Forest Survey of India (FSI 1996) were used to transform the volume of trees into biomass by multiplying it with specific gravity (FRI 1996). The sample of shrubs and herbs collected from sample plot were oven dried and dry weight was estimated. The Above Ground Biomass (AGB) was calculated for different components e.g. trees, shrubs and herbs for each plot-wise. The sum of trees, shrubs and herbs layer biomass (t/ha) were taken as total AGB of the plot.

Remote Sensing Data

The remote sensing imagery Landsat Thematic Mapper (TM), October 2009 was used in the study. All images were processed in ERDAS Image Processing software 2011.

Vegetation Indices

Vegetation indices are the mathematical transformation of the original spectral reflectance which are most commonly used to produce estimates of biomass (Hurcom and Harrison 1998; Foody et al. 2003; Zheng et al. 2004; Schlerf et al. 2005). The six vegetation indices used in this study are shown below in the Table 1. Normalized difference vegetation index (NDVI), Renormalized Difference Vegetation Index (RDVI), Modified Simple Ratio (MSR) and Difference

Vegetation Index (DVI) are slope based vegetation indices which are widely used. Modified soil adjusted vegetation index (MSAVI) and optimized soil adjusted vegetation index (OSAVI) are soil adjusted vegetation indices which are used for reducing the effect of soil background reflectance.

Correlation Analysis

Correlation analysis measures the degree of association between two or more variables. In this research, correlation analysis was used to assess the correlation between different vegetation indices and above ground biomass (AGB) from sample plot. A comparative study of different R^2 was done to

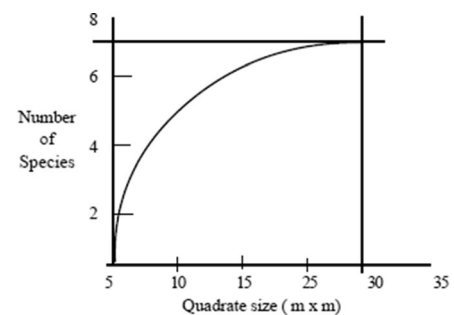


Fig 2 Species area curve

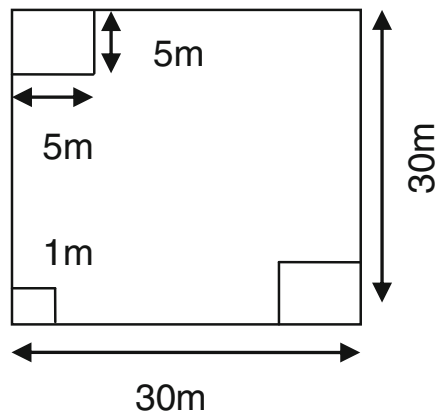


Fig 3 Field plot design

obtain best fit amongst different vegetation indices with AGB from sample plots.

Geostatistical Approach

Geostatistical methods are based on statistical models which are useful in modeling spatial variability through prediction and simulation (Goovaerts 1997; Deutsch and Journel 1998). It involves of fitting a mathematical function to a specified number of points, or all points within a specified radius, to determine the output value. It is a multi-step process, it includes exploratory statistical analysis of the data, variogram modeling and creating a surface from sample points. Semivariogram has been used for fitting of the data. Based on the semivariogram, the geostatistical process derives optimal linear unbiased spatial prediction methods by minimizing mean-squared prediction error.

The exponential model was used as the model type. This model is applied when spatial autocorrelation decreases exponentially with increasing distance. Here the autocorrelation disappears completely only at an infinite distance. The exponential model is also a commonly used model. The choice of which model to use is based on the spatial autocorrelation of the data and on prior knowledge of the phenomenon. The number of lags for the Variogram was 12.

In this study, co-kriging has been used for generating biomass layer. The co-kriging method is discussed in detail below. Co-kriging (CoK) is an extension of kriging. It uses multiple datasets and is very flexible, allowing you to investigate graphs of cross-correlation and autocorrelation. Co-kriging is a very versatile and rigorous statistical technique for spatial point estimation when both primary and auxiliary attributes are available. Co-Kriging uses statistical models that allow a variety of map outputs including predictions, prediction standard errors, probability, etc.

The best predictor along with geostatistical methods (Co-Kriging) were used to model biomass in the study area and to create continuous biomass maps. This systematic geostatistical approach is summarized in a flow chart (Fig. 4), which considers the associations between biomass and vegetation indices into the process of spatial prediction.

Results & Discussion

Descriptive Statistics of Study Sites

The descriptive statistics of above-ground biomass, measured during field work are shown in Table 2. The study area has biomass per hectare ranging from 0.23 to 250.69 t/ha.

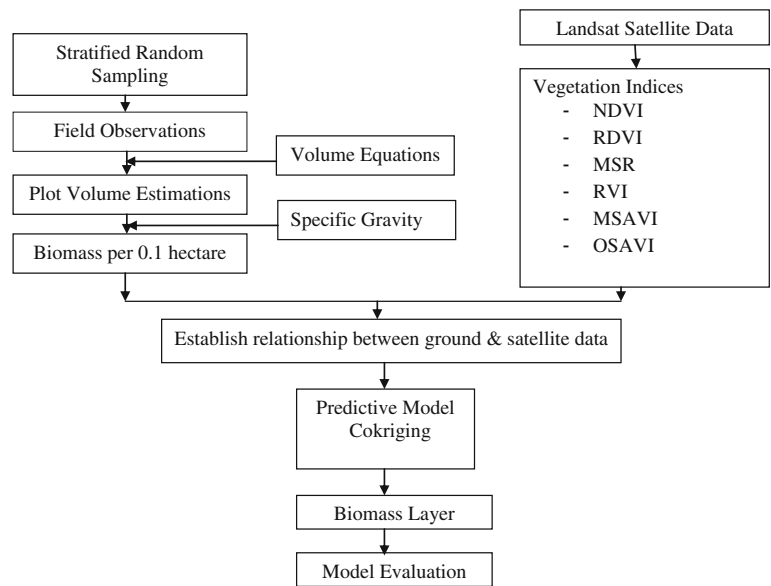
Correlation Analysis Between Above-ground Biomass and Remote Sensing Data

The results of correlation analysis between above ground biomass (AGB) and vegetation indices are presented in Table 3. The linear model function was used to obtain best fit correlation coefficients. The best fit correlation was seen in NDVI with a coefficient of determination (R^2) value of 0.610 shown in Fig. 5. The result shows that there is good correlation between biomass and vegetation indices. The NDVI vegetation index showed the best regression with above ground biomass (AGB), hence it was subsequently used as predictor in geostatistical prediction method.

Table 1 Equations of the vegetation indices

Vegetation Index	Equation	Reference
Ratio vegetation index (RVI)	$RVI = \frac{R_{RED}}{R_{NIR}}$	Pearson and Miller (1972)
Normalized difference vegetation index (NDVI)	$NDVI = \frac{R_{NIR} - R_{Red}}{R_{NIR} + R_{Red}}$	Rouse et al. (1974)
Renormalized difference vegetation index (RDVI)	$RDVI = (R_{NIR} - R_{Red}) / \sqrt{R_{NIR} + R_{Red}}$	Roujean and Breon (1995)
Modified Simple Ratio (MSR)	$MSR = \left(\frac{R_{NIR}}{R_{RED}} - 1 \right) / \left(\left(\frac{R_{NIR}}{R_{RED}} \right)^{1/2} + 1 \right)$	Chen (1996)
Modified soil adjusted vegetation index (MSAVI)	$MSAVI = \frac{1}{2} \left[2R_{NIR} + 1 - \sqrt{(2R_{NIR} + 1)^2 - 8(R_{NIR} - R_{RED})} \right]$	Qi et al. (1994)
Optimized soil adjusted vegetation index (OSAVI)	$OSAVI = (1 + 0.16)(R_{NIR} - R_{Red}) / (R_{NIR} + R_{Red} + 0.16)$	Rondeaux et al. (1996)

Fig 4 Methodology Flowchart



Predictive Modeling

In the current study based on the field inventory data, cokriging method was applied to estimate the biomass in which vegetation indices derived from satellite data were used as predictor variables for spatial prediction. The Geo-statistical analyst of Arc-GIS 9.3 software has been used for the formation of biomass layer using Ordinary Co-Kriging method. In Co-Kriging two datasets are used. The first dataset taken is that of biomass values and second dataset used was that of NDVI values. The best fit correlation was seen in NDVI with a coefficient of determination (R²) value of 0.610 shown in Fig. 5. The result shows that there is good correlation between biomass and vegetation indices. The NDVI vegetation index showed the best regression with above ground biomass (AGB), hence it was subsequently used as predictor in geostatistical prediction method so NDVI was used for second dataset. Box- Cox transformation was applied to enable the dataset to exhibit a normal distribution. The second order polynomial was used for removing the trend in the case of both the datasets. The biomass value dataset was used as variance and the NDVI as Covariance. The exponential model was used as the model type. This model is applied when spatial autocorrelation decreases exponentially with increasing distance.

Here the autocorrelation disappears completely only at an infinite distance. The exponential model is a commonly used model. The choice of which model to use is based on the spatial autocorrelation of the data and on prior knowledge of the phenomenon. The number of lags for the variogram was 12. The Fig. 6 and 7 represent the semi-variogram, the covariance and the predicted value graph for Co-Kriging. The regression function applied is shown : Regression Function: 0.295X+ 15.281. Based on the regression equation, y=0.295X+15.281 the model was run with on the Landsat satellite image of Ratnagiri district study area for biomass mapping. The result of the biomass spatial prediction map is discussed below and presented in Fig. 8.

Model Evaluation of the Spatial Prediction Methods for Above-ground Biomass

In this study, geostatistical model was developed and applied for biomass prediction. It is necessary to validate the model and to check the efficiency. We applied cross-validation to assess the performance of cokriging in estimating the spatial distribution of biomass. The basic statistics such as mean error (ME), average standard error and the root mean squared error (RMSE) shown in Eqs. 1,2 and 3 were applied to check the efficiency of model in spatial predictions of biomass in this region. These statistical methods measure the difference between the known data and the predicted data, thus assess the performance and accuracy of model predictions.

Table 2 Statistical characteristics of sampling plots

Parameter	Biomass (ton/ha)
Minimum	0.23
Average	59.18
Standard deviation	5.85
Maximum	250.69
Number	59

$$ME = \frac{1}{N} \sum_{i=1}^N (\hat{e}_i - e_i) \tag{1}$$

Table 3 Correlation coefficient (R^2) between vegetation indices and biomass

Vegetation Indices	NDVI	RDVI	MSR	RVI	MSAVI	OSAVI
Correlation coefficient (R^2)	0.610	0.602	0.599	0.594	0.483	0.574

Fig 5 Relationship between NDVI and above ground biomass

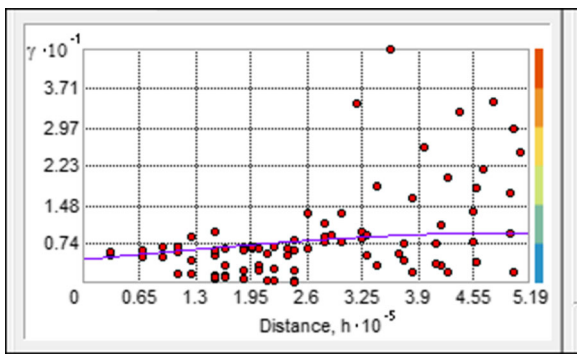
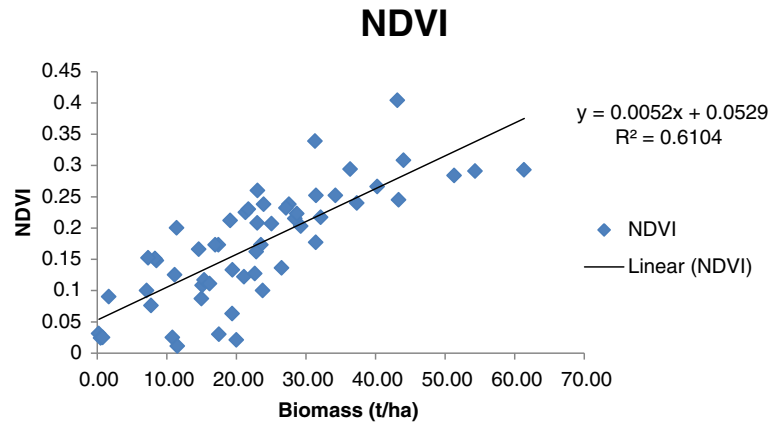


Fig 6 Semi-variogram for biomass

$$Average\ standard\ error = \sqrt{\frac{1}{N} \sum_{i=1}^N (\hat{e}_i - e_i)^2} \quad (3)$$

where N is size of the sample in the dataset, \hat{e}_i is the forecast estimated biomass value, e_i is the biomass values measured on the validation plots and \bar{e} is the mean of biomass values of the sample. The summary statistics of biomass estimation from spatial prediction methods is shown in Table 2. The mean error should ideally be zero if the interpolation method is unbiased. The mean error for biomass estimations is -0.078 which suggest that prediction is slightly biased. The standard errors are accurate when root-mean-square standardized prediction error is close to 1. The root-mean-square standardized prediction error is 0.967 which is close to 1 indicating good accuracy. The root-mean-square error and average standard error should be as small as possible. There is slight difference between predicted and measure value

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (\hat{e}_i - e_i)^2} \quad (2)$$

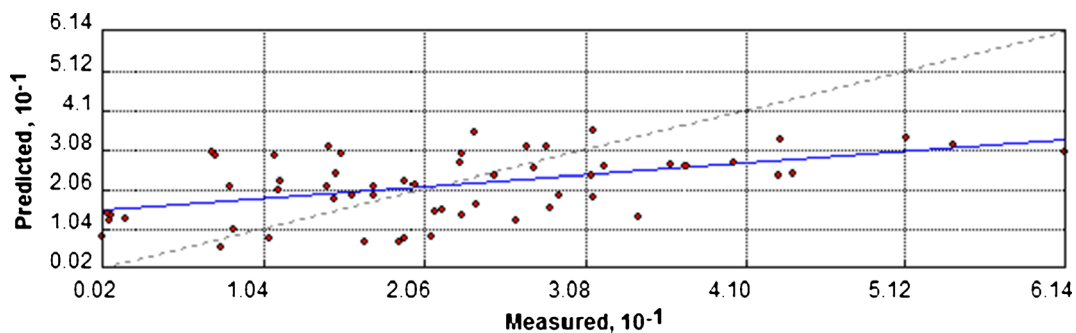
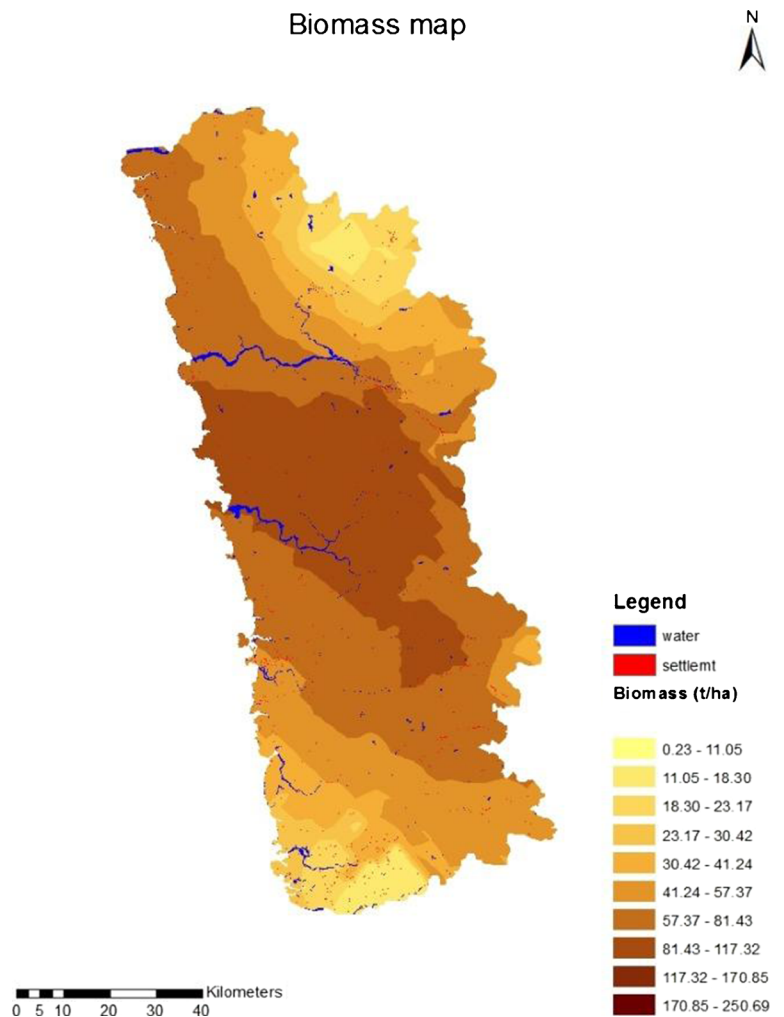


Fig 7 Graph of predicted values for biomass

Fig 8 Above ground biomass (ton/ha) prediction map



which can be indicated by root-mean square error and average standard error shown in Table 4.

Conclusions

The presented work demonstrate systematic approach of geostatistical prediction and mapping by integrating Landsat data, ground inventory, and GPS data for generating estimates of spatial biomass distribution. The maximum value of vegetation biomass was estimated to the value of 250.69 t/ha in semi evergreen forest and minimum biomass value was found to be 0.23 ton/ha in scrub land. Cokriging (CoK) is an

optimum method for spatial interpolation to estimate biomass. The result of aboveground biomass was validated using statistical error methods. The result shows that cokriging (CoK) method had smaller statistical error values. Other geostatistical methods such IDW and Spline are deterministic interpolation methods and hence doesn't provide assessment of errors with predicted values and IDW can produce "bulls eyes" around data locations. Spline are useful for smooth & continuous surfaces such as elevation and water table rather than estimation of biomass distribution, hence cokriging is the most appropriate method among the different kriging methods for spatial interpolation of biomass in this research. The present study can be used as baseline information for further temporal studies of biomass status of the region and in planning of forest and natural resources management.

Table 4 Prediction errors for biomass estimation model

	Mean error	Root-Mean-Square error	Average Standard error	Root-Mean Square Standardized
Cokriging	0.078	8.032	7.982	0.967

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References

- Akhavan, R., & Kia-Daliri, H. (2010). Spatial variability and estimation of tree attributes in a plantation forest in the Caspian region of Iran using geostatistical analysis Caspian. *Journal of Environmental Sciences*, 8, 163–172.
- ANSAB, (2010). Forest Carbon Stock Measurement (1st ed.). Kathmandu, Nepal: ANSAB, FECOFUN, ICIMOD.
- Berterretche, M., Hudak, A. T., Cohen, W. B., Maiersperger, T. K., Gower, S. T., & Dungan, J. (2005). Comparison of regression and geostatistical methods for mapping Leaf Area Index (LAI) with Landsat ETM + data over a boreal forest. *Remote Sensing of Environment*, 96(1), 49–61.
- Borah, N., Nath, A. J., & Das, K. A. (2013). Aboveground Biomass and Carbon Stocks of Tree Species in Tropical Forests of Cachar District, Assam, Northeast India. *International Journal of Ecology and Environmental Sciences*, 39(2), 97–106.
- Brown, S. (2002). Measuring carbon in forests: current status and future challenges. *Environmental Pollution*, 116(3), 363–372.
- Burrough, P. A. (1986). *Principles of geographical Information Systems for land resource assessment, Monographs on soil and resources survey, Number 12*. Oxford, UK: Oxford Science.
- Cerbu, G. A., Swallow, B. M., & Thompson, D. Y. (2011). Locating REDD: A global survey and analysis of REDD readiness and demonstration activities. *Environmental Science & Policy*, 14(2), 168–180.
- Chen, J. (1996). Evaluation of vegetation indices and modified simple ratio for boreal applications. *Canadian Journal of Remote Sensing*, 22, 229–242.
- Chirici, G., Barbati, A., & Maselli, F. (2007). Modeling of Italian forest net primary productivity by the integration of remotely sensed and GIS data. *Forest Ecology and Management*, 246(2), 285–295.
- Dadhwal, V.K., Singh, S., Patil, P., (2009). Assessment of phytomass carbon pools in forest ecosystems in India. NNRMS Bulletin. 41–57
- Deutsch, C. V., & Journel, A. G. (1998). *Geostatistical Software Library and User's Guide* (2nd ed.). New York, USA: Oxford University Press.
- Devagiri, G. M., Money, S., Singh, S., Dadhawal, V. K., Patil, P., Khaple, A., Devakumar, A. S., & Hubballi, S. (2013). Assessment of above ground biomass and carbon pool in different vegetation types of south western part of Karnataka, India using spectral modeling. *Tropical Ecology*, 54(2), 149–165.
- Devi, L. S., & Yadava, P. S. (2009). Aboveground biomass and net primary production of semi-evergreen tropical forest of Manipur, North-Eastern India. *Journal of Forestry Research*, 20, 151–155.
- FAO. (2010). *Global forest resources assessment: main report*. Rome: Food and Agriculture Organization of the United Nations.
- Foody, G. M., Boyd, D. S., & Cutler, M. E. J. (2003). Predictive relations of tropical forest biomass from Landsat TM data and their transferability between regions. *Remote Sensing of Environment*, 85(4), 463–474.
- FRI. (1996). *Indian Woods*. Dehradun: Forest Research Institute.
- FSI. (1996). *Volume equations for forests of India, Nepal and Bhutan, Forest Survey of India, Ministry of Environment and Forests*. Dehradun: Govt. of India.
- García-Martín, A., Pérez-Cabello, F., de la Riva, J. R., & Montorio, R. (2008). Estimation of crown biomass of Pinus spp. from Landsat TM and its effect on burn severity in a Spanish fire scar. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 1(4), 254–265.
- Gibbs, H. K., Brown, S., Niles, J. O., & Foley, J. A. (2007). Monitoring and estimating tropical forest carbon stocks: making REDD a reality. *Environmental Research Letters*, 2(2007), 1–13.
- Goovaerts, P. (1997). *Geostatistics for Natural Resources Evaluation*. New York, USA: Oxford University Press, Inc.
- Hese, S., Lucht, W., Schullius, C., Barnsley, M., Dubayah, R., Knorr, D., Neumann, K., Riedel, T., & Schröter, K. (2005). Global biomass mapping for an improved understanding of the CO₂ balance—the Earth observation mission Carbon-3D. *Remote Sensing of Environment*, 94(1), 94–104.
- Hurcom, S. J., & Harrison, A. R. (1998). The NDVI and spectral decomposition for semi-arid vegetation abundance estimation. *International Journal of Remote Sensing*, 19(16), 3109–3125.
- Kale, M. P., Singh, S., Roy, P. S., & Ravan, S. A. (2009). Patterns of carbon sequestration in forests of Western Ghats and study of applicability of remote sensing in generating carbon credits through afforestation/reforestation. *Journ. Indian Soc. Rem. Sens*, 37(2), 457–471.
- Krankina, O. N., Bergen, K. M., Sun, G., Masek, J. G., Shugart, H. H., & Kharuk, V. (2004). Remote sensing of Boreal Forest in selected regions. *Land change science*, 6, 123–138.
- Kumar, R., Gupta, S. R., Singh, S., Patil, P., & Dhadhwal, V. K. (2011). Spatial distribution of forest biomass using remote sensing and Regression models in Northern Haryana, India. *International Journal of Ecology and Environmental Sciences*, 37, 37–47.
- Lu, D. (2005). Above ground biomass estimation using Landsat TM data in the Brazilian Amazon. *International Journal of Remote Sensing*, 26(12), 2509–2525.
- Maselli, F., & Chiesi, M. (2006). Evaluation of Statistical Methods to Estimate Forest Volume in a Mediterranean Region. *IEEE Transactions on Geoscience and Remote Sensing*, 44, 2239–2250.
- Maynard, C. L., Lawrence, R. L., Nielsen, G. A., & Decker, G. (2007). Modeling vegetation amount using bandwise regression and ecological site descriptions as an alternative to vegetation indices. *GIScience and Remote Sensing*, 44(1), 68–81.
- McRoberts, R. E., Tomppo, E. O., & Næsset, E. (2010). Advances and emerging issues in national forest inventories. *Scandinavian Journal of Forest Research*, 25, 368–381.
- Meng, Q., Cieszewski, C., & Madden, M. (2009). Large area forest inventory using Landsat ETM+: a geostatistical approach. *ISPRS Journal of Photogrammetry and Remote Sensing*, 64(1), 27–36.
- Mohanraj, R., Saravanan, J., & Dhanakumar, S. (2011). Carbon stock in Kolli forests, Eastern Ghats (India) with emphasis on aboveground biomass, litter, woody debris and soils. *Forest*, 4, 61–65.
- Nanos, N., Calama, R., Montero, G., & Gil, L. (2004). Geostatistical prediction of height/diameter models. *Forest Ecology and Management*, 195, 221–235.
- Palmer, D. J., Höck, B. K., Kimberley, M. O., Watt, M. S., Lowe, D. J., & Payn, T. W. (2009). Comparison of spatial prediction techniques for developing Pinus radiata productivity surfaces across New Zealand. *Forest Ecology and Management*, 258(9), 2046–2055.
- Pearson, R. L., & Miller, L. D. (1972). Remote mapping of standing crop biomass for estimation of the productivity of the short-grass Prairie, Pawnee National Grassland, Colorado: 8th international symposium on remote sensing of environment, p. 1357–1381.
- Qi J., Chehbouni A., Huete A. R., Kerr Y. H. (1994). Modified Soil Adjusted Vegetation Index (MSAVI). *Remote Sensing and Environment* 48, 119–126.
- REDD. (2009). The United Nations Collaborative Programme on Reducing Emissions from Deforestation and Forest Degradation in Developing Countries.
- Rondeaux, G., Steven, M., & Baret, F. (1996). Optimisation of the Soil-Adjusted Vegetation Indices. *Remote Sensing of Environment*, 55, 95–107.
- Roujean, J. & Breon, F. (1995). 'Estimating PAR absorbed by vegetation from bidirectional reflectance measurements'. *Remote Sensing of Environment*, 51, 375–384.
- Rouse, J. W., Haas, R. H., Schell, J. A., Deering, D. W., & Harlan, J. C. (1974). Monitoring the vernal advancement of retrogradation of natural vegetation, Greenbelt, MD, NASA/GSFC, type III, final report, p. 371.

- Sales, M. H., Souza, C. M., Jr., Kyriakidis, P. C., Roberts, D. A., & Vidal, E. (2007). Improving spatial distribution estimation of forest biomass with geostatistics: a case study for Rondônia, Brazil. *Ecological Modelling*, 205(2007), 221–230.
- Schlerf, M., Alzberger, C., & Hill, J. (2005). Remote sensing of forest biophysical variables using HyMap imaging spectrometer data. *Remote Sensing of Environment*, 95(2005), 177–194.
- Srinath, K. (2008). *Assessment of Carbon Sequestration in Sacred Groves of Kodagu*. M.Sc. Thesis. Bangalore: University of Agricultural Sciences.
- Tan, K., Pio, S., Peng, C., & Fang, J. (2007). Satellite based estimation of biomass carbon stocks for northeast China's forest between 1982 and 1999. *Forest Eco. and Manage*, 240(2007), 114–121.
- Thakur, T., & Swamy, S. L. (2010). Analysis of land use, diversity, biomass, C and nutrient storage of a dry tropical forest ecosystem of India using satellite remote sensing and GIS techniques. *International Forestry and Environment Symposium*, 15, 273–278.
- Tiwari, A. K., & Singh, J. S. (1984). Mapping forest biomass in India through aerial photographs and nondestructive field sampling. *Applied Geography*, 4, 151–165.
- USAID (Writer). (2009). *Forests and Climate Change Toolbox*.
- Zhao, M., & Zhou, G. S. (2005). Estimation of biomass and net primary productivity of major planted forests in china based on forest inventory data. *Forest Ecology and Manage*, 207(3), 295–313.
- Zheng, D., Rademacher, J., Chen, J., Crow, T., Bresee, M., Le Moine, J., & Ryu, S. (2004). Estimating aboveground biomass using Landsat 7 ETM + data across a managed landscape in northern Wisconsin, USA. *Remote Sensing of Environment*, 93(3), 402–411.