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An alternative approach for estimating above ground biomass using Resourcesat-2 satellite data and artificial neural network in Bundelkhand region of India

Dibyendu Deb · J. P. Singh · Shovik Deb · Debajit Datta · Arunava Ghosh · R. S. Chaurasia

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Abstract Determination of above ground biomass (AGB) of any forest is a longstanding scientific endeavor, which helps to estimate net primary productivity, carbon stock and other biophysical parameters of that forest. With advancement of geospatial technology in last few decades, AGB estimation now can be done using space-borne and airborne remotely sensed data. It is a well-established, time saving and cost effective technique with high precision and is frequently applied by the scientific community. It involves development of allometric equations based on correlations of ground-based forest biomass measurements with vegetation indices derived from remotely sensed data. However, selection of the best-fit and explanatory models of biomass estimation often becomes a difficult proposition with respect to the image data resolution (spatial and spectral) as well as the sensor platform position in space. Using Resourcesat-2 satellite data and Normalized Difference Vegetation Index (NDVI), this pilot scale study compared traditional linear and nonlinear models with an artificial intelligence-based non-parametric technique, i.e. artificial neural network (ANN) for formulation of the best-fit model to determine AGB of forest of the Bundelkhand region of India. The results confirmed the superiority of ANN over other models in terms of several statistical significance and reliability assessment measures. Accordingly, this study proposed the use of ANN instead of traditional models for determination of AGB and other bio-physical parameters of any dry deciduous forest of tropical sub-humid or semi-arid area. In addition, large numbers of sampling sites with different quadrant sizes for trees, shrubs, and herbs as well as application of LiDAR data as predictor variable were recommended for very high precision modelling in ANN for a large scale study.

Keywords Above ground biomass · Allometric equation · Artificial neural network · Normalized difference vegetation index · Satellite image

D. Deb · J. P. Singh · R. S. Chaurasia
Indian Grassland and Fodder Research Institute, Gwalior Road, Jhansi 284 003, India

S. Deb (✉)
Department of Soil Science and Agricultural Chemistry, Uttar Banga Krishi Viswavidyalaya, Cooch Behar 736 165, India
e-mail: shovikiitkgp@gmail.com

D. Datta
Department of Geography, Jadavpur University, Kolkata 700032, India

A. Ghosh
Department of Agricultural Statistics, Uttar Banga Krishi Viswavidyalaya, Cooch Behar 736 165, India

Introduction

Above ground biomass (AGB) is widely considered to be a key indicator of forest vegetal health and related seral stages (Brown et al. 1997; Yen 2015; Luo et al. 2017). In spite of the fact that direct measurement of AGB of a forest area is the most accurate technique with respect to other ones, it is considerably laborious, time consuming, and expensive at one end as well as involves destructive sampling of trees at the other (Basuki et al. 2009). Besides, legislations of most of the countries including India do not permit large-scale felling of forest trees at the present geo-environmental conditions (Datta and Chatterjee 2012). Alternatively, AGB can also be indirectly estimated using remotely sensed geospatial data, which is capable of covering large span of area in lesser time and cost (Sharma et al. 2013; Ogaya et al. 2015). In this regard, satellite data derived vegetation indicators had been developed by the scientific community in the recent past to classify and monitor vegetation dynamics (Casanova et al. 1998; Balzarolo et al. 2016). The Normalized Difference Vegetation Index (NDVI) is one such frequently used vegetation indicator derived from satellite data for measuring the photosynthetic activities at landscape scales and can be effectively used to estimate AGB and net primary productivity (NPP) (Nemani et al. 2003; Cho et al. 2007).

The NDVI also effectively responds to the changes in the amount of green biomass, chlorophyll content and canopy level water stress (Mutanga and Skidmore 2004). Since, there is an obvious relationship between forest biomass and vegetation indices, AGB can be estimated using allometric regression equations involving NDVI with satisfactory accuracy (Cho et al. 2007). However, it is not feasible to develop elementary predictive equations easily and researchers have to use the most common or hitherto published regression equations which appear most appropriate to them as per the needs (Nemani et al. 2003; Mutanga and Skidmore 2004). Few of these equations are either linear, multiple linear regressions or correlations; and others are curvilinear relations like power, exponential or polynomial functions (Datta and Chatterjee 2012; Chave et al. 2014). However, linear relations are rather rare entities in ecological modelling and most popularly used functions are the curvilinear ones (Paine et al. 2012). Conversely, the concept of artificial neural network (ANN) was conceived nearly 50 years ago but it is during the last 20 years that the computational tool for ANN has been developed to handle practical problems and accordingly applied extensively in the fields of forestry, landscape ecology, hydrological modelling, terrain characterization etc. (Dutta et al. 2004; Nefeslioglu et al. 2008). Limited studies also used ANN to determine forest AGB (Foody et al. 2003; Englhart et al. 2012; Vahedi 2016). In general, ANN imitates the structure, information processing patterns and knowledge acquisition processes of the human nervous system. For these reasons, ANN has emerged as a remarkably powerful and efficient tool in ecological applications and for data modelling compared to other conventional regression-based procedures (Evrendilek et al. 2013; Vahedi 2016).

In the present study, a comparative evaluation of an ANN-based model to other conventional models of AGB estimation from remotely sensed data has been performed taking few districts of Indian states of Madhya Pradesh and Uttar Pradesh. These districts are mostly dominated by the dry deciduous forests and popularly conceived as parts of the Bundelkhand region of central India (Singh et al. 2013). As per the authors' knowledge, this kind of ANN-based estimation of AGB has not been conducted till date for the dry deciduous forests like that of the selected study area. Considering this research gap, the prime objectives of this study were designed as (i) to test the performance of the ANN model in estimating AGB with respect to field based measurements and (ii) to compare the performance of the ANN model with several other frequently used models in similar studies.

Methodology

Study area

For this study, 6 districts of Madhya Pradesh namely Guna, Vidisha, Shivpuri, Datia, Tikamgarh, Chhatarpur and 7 districts of Uttar Pradesh viz. Jhansi, Lalitpur, Jalaun, Hamirpur, Mahoba, Fatehpur and Banda were selected (Fig. 1). The entire area falls under the central highland physiographic zone of India and lies within 23° 00′ N to 26° 30′ N latitudes and 76° 30′ E to 81° 30′ E longitudes (Sheikh et al. 2011). The region has sub-humid to semi-arid bio-climate with mean annual precipitation varying from 75 cm in the north to 125 cm in the southeast (Bhattacharyya et al. 2008; Gupta et al. 2014). However, the temporal rainfall distribution is erratic and concentrated in monsoon months mainly (Gupta et al. 2014).

Vegetation of the area is dominated by varieties of dry deciduous forests with interspersed grasslands (Kale et al. 2004) (Fig. 2). Presence of extreme climatic condition and shallow Vindhyan soils have given rise to dry teak (*Tectona grandis*) and dry mixed deciduous forests (Majumdar 2008). Besides these major vegetation types, other frequently found ones are open grasslands, open woodlands with tall grasses and thorny woodlands (Kale

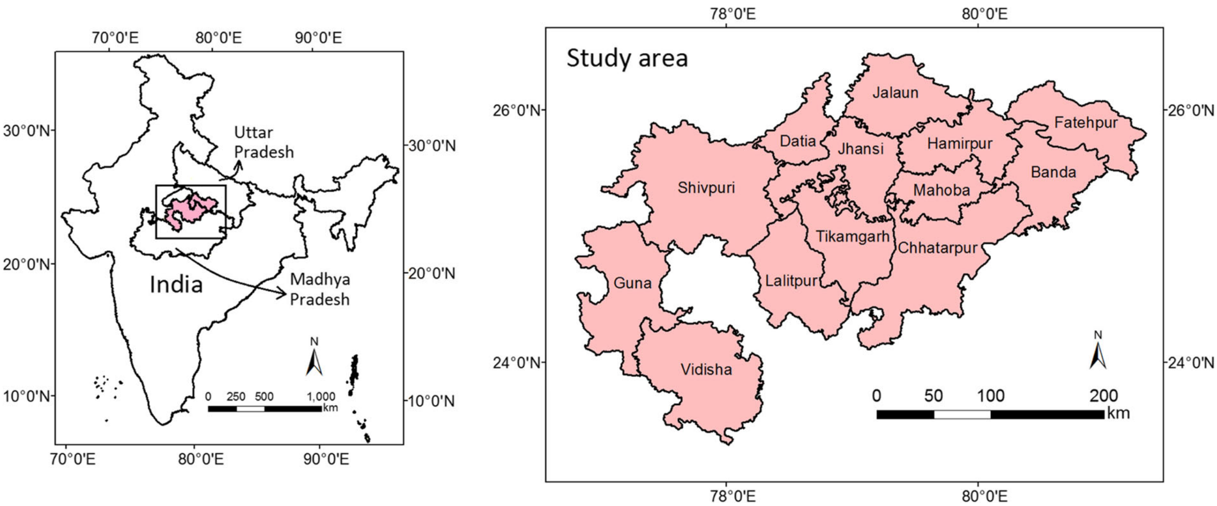

Fig. 1 Location map of the study area

et al. 2004). In particular, dominating species are *Tectona grandis, Anogeissus pendula, Azadirachta indica, Dalbergia sissoo, Butea monosperma, Boswellia serrata, Acacia catechu, Bauhinia racemosa, Lannea coromandelica, Anogeissus latifolia, Diospyros melanoxylon, Buchanania lanzan, Aegle marmelos, Madhuca indica, Terminalia bellerica* etc. (Kale et al. 2004). Some herbs and shrubs species which can be frequently spotted throughout the study area are *Carissa opaca, Nyctanthus arbor-tristis, Cassia tora, Lantana camara, Ziziphus nummularia* etc. (Majumdar 2008). As the forests are in low productivity belt (NPP wise), they are subjected to biotic pressure and overexploitation by local people through shifting cultivation, fires, grazing, lopping etc. (Sarkar 2008). The meager availability of natural resources in

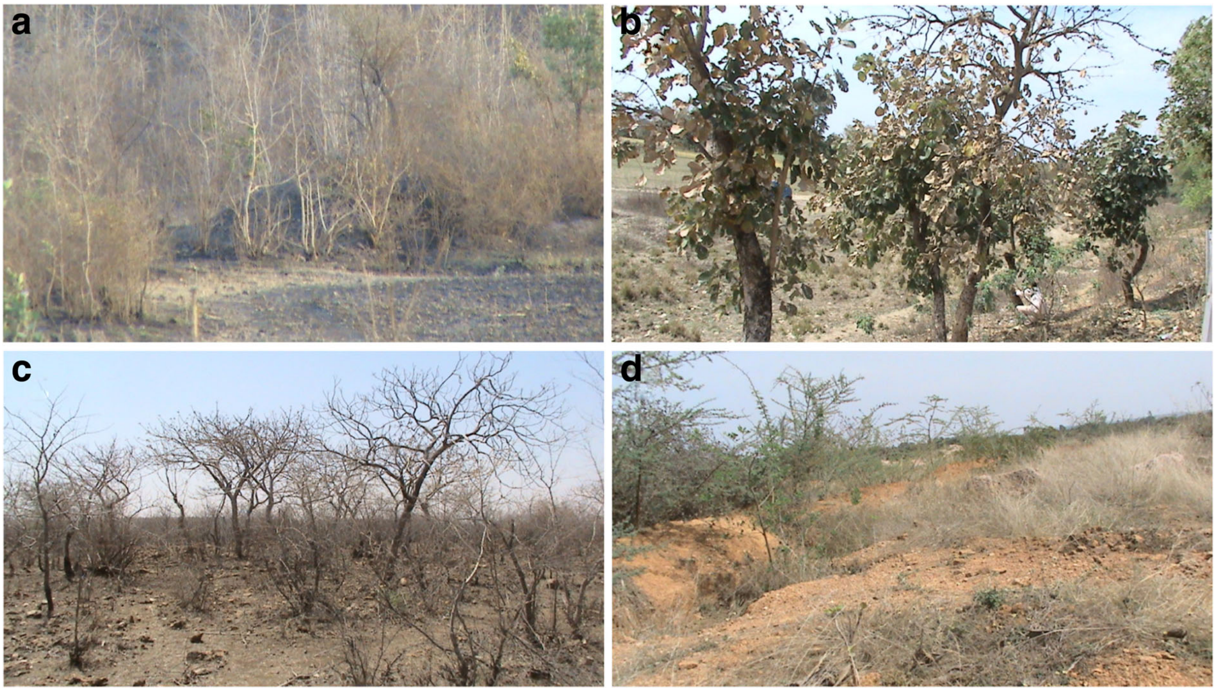

Fig. 2 The types of forest cover of the study area. **a** Kardhai (*Anogeissus pendula*) dominated mixed dense forests. **b** Palas (*Butea monosperma*) forests. **c** Dry deciduous scrub dominated by Khair (*Acacia catechu*). **d** Ravine thorn forests

the area has added more stress to the forests from the ecological point of view.

Satellite data and processing

Following the aim to develop regression models, which will serve as functional relationships to estimate AGB directly from satellite data, this study choose remotely sensed Advanced Wide Field Sensor (AWiFS) data (containing 4 spectral bands) of Resourcesat-2 satellite (spatial resolution 56 m, swath 741 km). The data were geo-referenced and orthorectified from the end of producers (Resourcesat-2 Handbook 2016). The satellite images (Resourcesat-2, AWiFS, row 55 and path 100) (acquired on February, 2013) were obtained from National Remote Sensing Centre, Indian Space Research Organisation. The whole image processing was conducted by ERDAS IMAGINE 9.1 software. For further image corrections, Survey of India (SOI) topographic maps (sheet no. 54 F, G, H, J, K, L, M, N, O, P; 55 I, M; 63 B, C, D, O) were used as well as 200 ground control points (GCPs) were identified by a Garmin GPS (Garmin 276, Garmin Ltd., Schaffhausen, Switzerland). Nearest neighbor algorithm was used for resampling of the images (Deb et al. 2014).

The rectified and enhanced images were used for vegetation index analysis. The most widely used vegetation index, NDVI (Datta and Deb 2012) was selected in this study as it has very high correlation with photosynthetically active vegetation (Hao et al. 2011). The standard equation for calculation of NDVI is as in Eq. 1:

$$\mathrm{NDVI} = \frac{\mathrm{NIR}-\mathrm{R}}{\mathrm{NIR}+\mathrm{R}} \tag{1}$$

where, NIR and R stand for reflectance of vegetation in infrared and red band, respectively.

Field data collection

The sampling design and selection of sample sites were broadly based on (i) forest density as per Forest Survey of India (FSI) maps and (ii) NDVI values as per AWiFS data (ISFR 2011). From the entire study area, total 31 sites were selected with different forest density and NDVI values. Within each of these sites, four plots of 0.1 ha size (31.61 m × 31.61 m) were selected for biomass estimation. For plot selection, the coordinates of the corresponding satellite image pixels were considered to avoid overlapping of pixels within a single plot. This resulted in maximum possible coverage of one plot by one AWiFS pixel. Within each plot, nested two stage sampling approach was adopted for measurement of trees (0.1 ha), shrubs (25 m^2) and herbs (1 m^2). Individual tree volume was calculated from the collected field data using site specific tree volume equations available in the literature of FSI (ISFR 2003). For the trees species with unknown volume equations, geometric relationships were used to approximate the volume of standing tree bole (Chen et al. 2007). Biomass of each tree was then worked out by multiplying with specific gravity and expansion factor (Gregoire et al. 2016; Mani and Parthasarathy 2007). Based on the available literature on field based indirect estimation of biomass of this region, mean biomass expansion factor (BEF) value of 1.5 was used for this study (Deb et al. 2016). The AGB of each plot was calculated by summing the phytomass of all the plant species (i.e. trees + shrubs + herbs) and then converting the obtained value per hectare basis. Geodatabase of AGB production was generated using ArcGIS 10.1 software.

Above ground biomass simulation from remotely sensed images

To correlate the spectral signatures of remotely sensed images with AGB, this study used linear regression as well as well recognized nonlinear models. Nonlinear models are the most commonly used tools to estimate biomass production as tree vegetation generally depicts nonlinear relationship with spectral reflectance data (Powell et al. 2010; Lai et al. 2013). Further, nonlinear models do not require large numbers of ground based observations on each experimental unit and can be accommodated by biologically meaningful parameters (Myers et al. 2001; Peek et al. 2002). Previous studies had established power model as one of the most suitable for explaining tree biomass as well as for measuring parameters like diameter at breast height, total tree height etc. (Whittaker and Marks 1975; Deb et al. 2016). Likewise, exponential model had also frequently been used for tree biomass estimation in an effective manner (Heath et al. 1996; Popescu 2007). Following these, power ($y = a^{*}x^{b}$) and exponential ($y = a^{*}e^{bx}$) models were selected as nonlinear model after necessary log transformation. Here, y is the estimated AGB or response variable; a and b are regression coefficients; and x is the spectral reflectance data (e.g. NDVI) functioning as predictor variable.

This study further used ANN, which is a nonparametric model and can analyze complex dataset without making any assumption about them (Kelsey and Neff 2014). The back propagation algorithm was used in this study to train ANN. It is one of the most successfully used algorithms to efficiently model numerous types of technical applications (Erzin and Cetin 2013; Tiryaki and Aydın 2014). In general, any ANN is consisted of 3 types of layers viz. one input layer, one hidden layer and an output layer comprising several neurons. The ANN used in this study was consisted of an input layer with n co-variates and an output layer with one output neuron. It calculated the function as in Eq. 2:

$$O(\mathrm{x}) = \mathrm{f}\left(\mathrm{w}_0 + \sum_{i=1}^{n} \mathrm{w}_i \mathrm{x}_i\right) = \mathrm{f}\left(\mathrm{w}_0 + \mathrm{w}^T \mathrm{x}\right) \quad (2)$$

where, w_0 denotes the intercept; $w = (w_1, w_2, \ldots, w_n)$ or the vector consisting of all synaptic weights without the intercept; and $x = (x_1, \ldots, x_n)$ or the vector of all covariates. It calculates the function as defined by Gunther and Fritsch (2010).

For all the models of this study, 80% of the data were selected by random sampling and allocated for model building while the rest 20% were set for validation following Snee (1977). The models were then tested based on few reliability statistics including the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), residual standard error (RSE) and coefficient of determination (R^2) (Akaike 1974; Aho et al. 2014). These indices are widely used in natural sciences (Aho et al. 2014; Burivalova et al. 2014) and have been expressed as:

$$\mathrm{AIC} = -2 \ln\left(l\left(\hat{\theta}\right)\right) + 2p \quad (3)$$

$$\mathrm{BIC} = -2 \ln\left(l\left(\hat{\theta}\right)\right) + p \ln n \quad (4)$$

$$\mathrm{RSE} = \sqrt{\sum_{i=1}^{n} \left(\bar{Y} - Y_i\right)^2 / n} \quad (5)$$

$$R^2 = 1 - {}^{SS_{res}}/_{SS_{tot}} \quad (6)$$

where, $l\left(\hat{\theta}\right)$ indicates the likelihood of the sample for the values estimated from the model parameters; p denotes the number of tree parameters estimated;   is overall mean; Yi is individual observation; SS_{res} and SS_{tot} means residual and total sum of squares respectively, and n is sample size.

All statistical analyses and modelling were done using the R 3.1.3 statistical software package. The Neuralnet package, which is generally applied for training multi-layer perceptions in regression analysis, was used for the present ANN model.

Results

Following the aims of the study, this work considered plot-wise biomass estimation in ground level within the study area. At the same time, calculation of the NDVI of the whole area was done based on the satellite images (Fig. 3a). The deviation in NDVI values (ranging from 0 to 0.7) over the images indicated variation in vegetation cover throughout the study area. In general, the darker colored areas meant higher vegetation covers and vice versa. Figure 3b represented a comparative scenario of the observed biomass derived from ground surveys (indicated by ring diameter) and respective NDVI values of the selected plots (indicated by colored value).

Correlation of ground data with NDVI values using linear and nonlinear model

In order to detect a correlation between the field-estimated AGB and corresponding NDVI values, Pearson's product-moment correlation test was used. According to the p value (< 0.01), the variables were significantly correlated. The correlation estimate was 0.94 showing potential for satisfactory fitting of the regression model. Further, taking NDVI values as the predictor variable and field-estimated AGB as response variable, linear regression analysis showed positive relationship with a RSE of 37.7 and R^2 value of 0.89 (Fig. 4, Table 1).

The field observed AGB and NDVI values were further used to fit two types of nonlinear models viz. a power and an exponential model (Fig. 5). The AIC, BIC, RSE and R^2 values of the models were considered as the determining parameter, where lower AIC and BIC values were indicated higher quality of statistical models for a given dataset and vice versa (Aho et al. 2014). Outcomes revealed that the power model (AIC = 280.4, BIC = 392.1, RSE = 20.9, R^2 = 0.94) as a marginally better fit than the exponential model (AIC = 294.4, BIC = 398.9, RSE = 26.2, R^2 = 0.90) to explain the

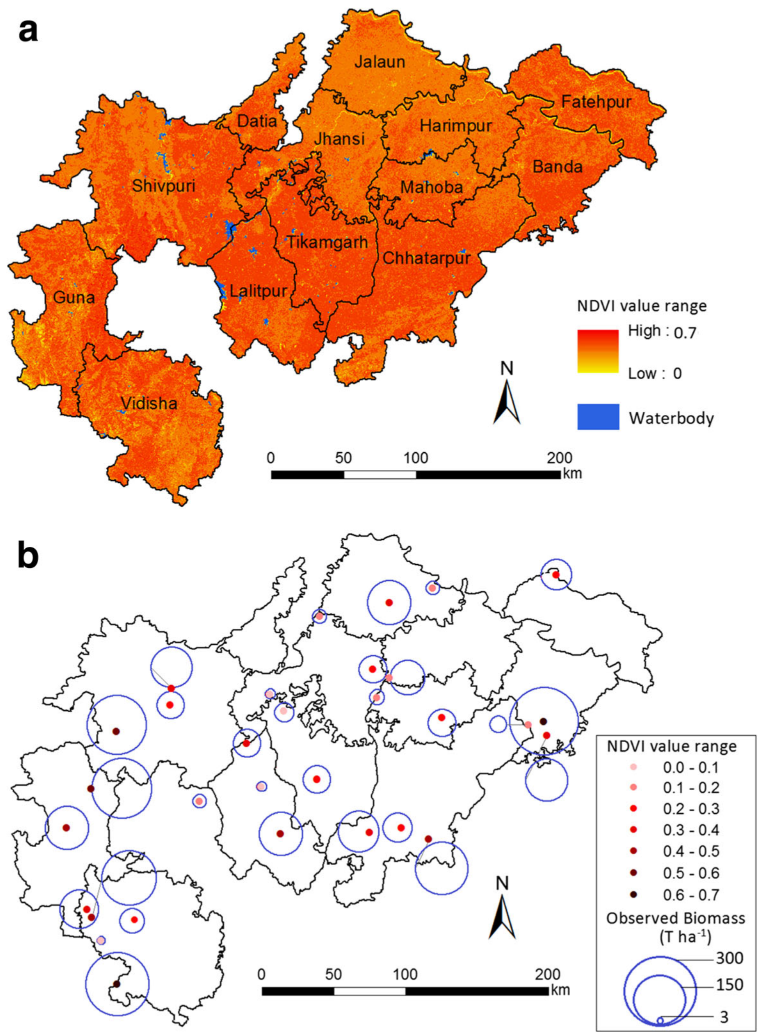

Fig. 3 **a** NDVI map of the study area. **b** Comparison of total observed biomass with NDVI values

relationship between NDVI and observed biomass (Table 1). However, both of these nonlinear models were found to be considerably better to describe the relationship of field-estimated AGB with NDVI values in comparison to the linear regression model as per AIC, BIC and RSE values (Table 1).

Use of ANN model

This study further considered ANN to fit the NDVI values (as predictor variable) with the field-estimated AGB (response variable). The ANN model always has an advantage to define the required number of hidden layers and hidden neurons according to the needed complexity of the problem (Gunther and Fritsch 2010). In the Neuralnet package of R software, 2 input nodes, 5 hidden neurons, and 4 transfer functions were accommodated which showed that the training process required 481 steps until all absolute partial derivatives of the error function became smaller than 0.01 (the default threshold). Figure 6 represented the structure of the trained neural network i.e. the network topology. The plot included trained synaptic weights as well as all intercepts. The estimated weight of ANN ranged from − 1.90 to 2.49. Here the intercepts for the hidden layer were ranged from − 1.46 to 3.27 and intercept for total biomass was 0.65.

This ANN was used to plot the NDVI values in a scatter graph against the observed AGB. The resultant fit-plot was flexible and closely followed the observed values (Fig. 7). Here, AGB was calculated in T ha^{-1} with its scale changed by dividing each value by the maximum observed value so that the logistic function could be applied as the activation function. This ANN

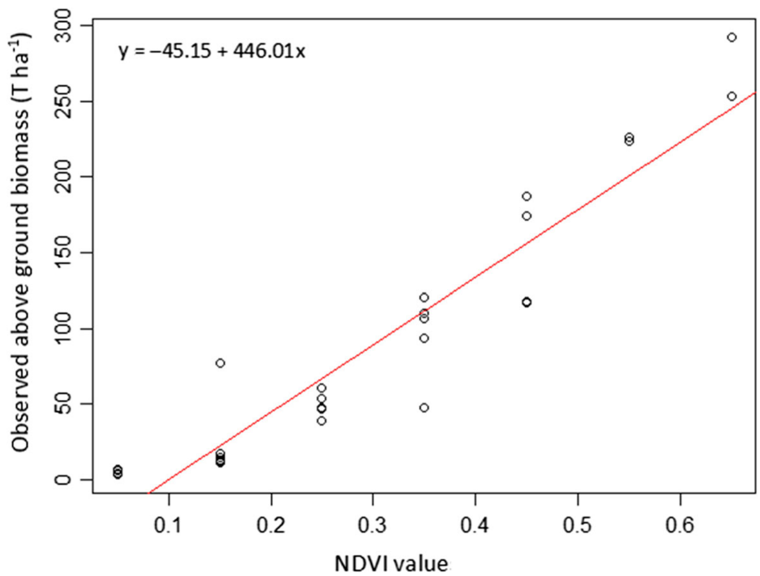

Fig. 4 Linear relationship of plot wise NDVI values with field estimated AGB

model had much lesser AIC (32.0), BIC (54.9) and RSE values (0.007) in comparison to the earlier tested non-linear models. The R^2 (0.98) was also notably higher (Table 1). These statistics had actually established that the ANN is a much better model to fit NDVI values with the field-estimated AGB of the plots.

After establishing the ANN as the best model to fit NDVI values with field-estimated biomass, this study applied the NDVI values to predict AGB of those plots as per ANN. The predicted biomass of the plots were further compared with the actual observed biomass (Fig. 8). It showed a high degree of correlation ($r = 0.97$, $p < 0.01$) between the predicted and observed AGB confirming the validation of the ANN model.

Discussion

This study clearly indicated the potential of satellite image-derived index to predict forest AGB. Figure 3 shows the similarities in the trend of NDVI values with the field-measured AGB. However, further research with different allometric models (including linear, non-linear and ANN) inferred the considerable superiority of ANN over the others to establish the relationship of NDVI values with AGB. Several studies have already been conducted on applicability of ANN in prediction of biophysical parameters of forests, considering field-measured dendometric variables as inputs (Ingram et al. 2005; Englhart et al. 2012; Vahedi 2016). However, usage of NDVI as input nodes in the ANN model to predict AGB is a rather new approach.

All the models compared in this study have their own advantages and limitations. It is easy to simulate any linear model. However, only recent development in softwares expanded the possibilities of using even traditional nonlinear models in ecological modelling (Ritz and Streibig 2008). Fitting a nonlinear model is always more challenging than linear one but the nonlinear models are flexible in terms of computing output (Paine et al. 2012). Contrariwise, using artificial intelligence systems like ANN to model AGB always has the

Table 1 Comparison of statistical parameters viz. Akaike information criterion (AIC), Bayesian information criterion (BIC), residual standard error (RSE) and coefficient of determination (R^2) of the different models

Models	AIC	BIC	RSE	R^2
Linear	407.8	412.9	37.7	0.89
Power	280.4	392.1	20.9	0.94
Exponential	294.4	398.9	26.2	0.90
ANN	32.0	54.9	0.007	0.98

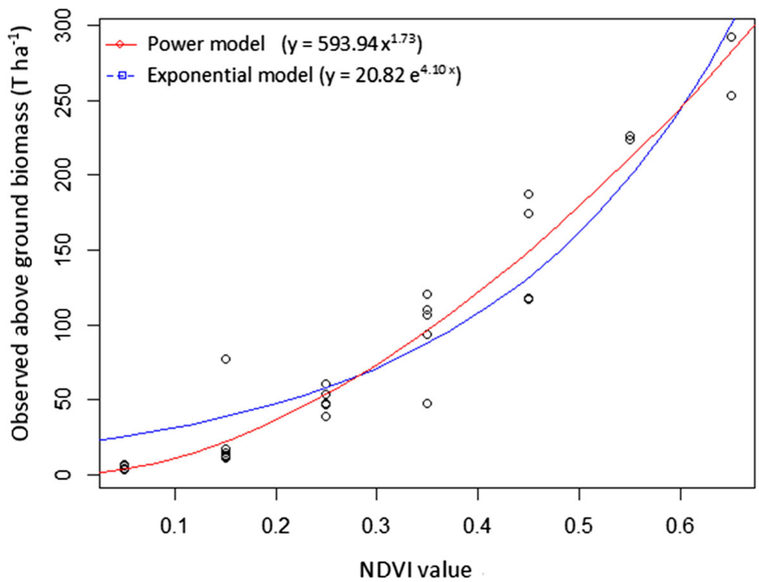

Fig. 5 Relationship of plot wise NDVI values with field estimated AGB as per nonlinear power and exponential models

possibility of over-fitting and keeping users in dark about the internal processes (Jain et al. 1996; Liu et al. 2010). Without a coherent mathematical equation, the output of ANN only has a 'black box' topology (Olden and Jackson 2002). However, the topology differs from one model to another and can be saved as a digital file in the computer for later use. In addition, ANN can be validated satisfactorily to avoid fitting problems by wise choice of network architecture and sufficient amount of training and testing datasets. Hence, the role of the model builder becomes highly imperative here with the need of noteworthy a priori knowledge on the study site characteristics and ecological dynamics.

It is to be noted that remotely sensed vegetal reflectance data and subsequently derived indices like the NDVI are always subject to notable variations under

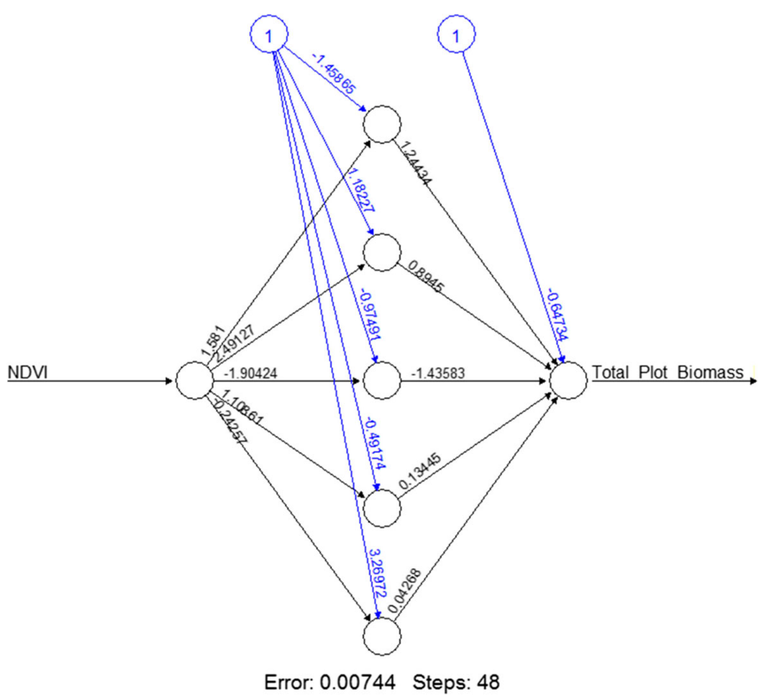

Fig. 6 The structure of the trained neural network used in this study

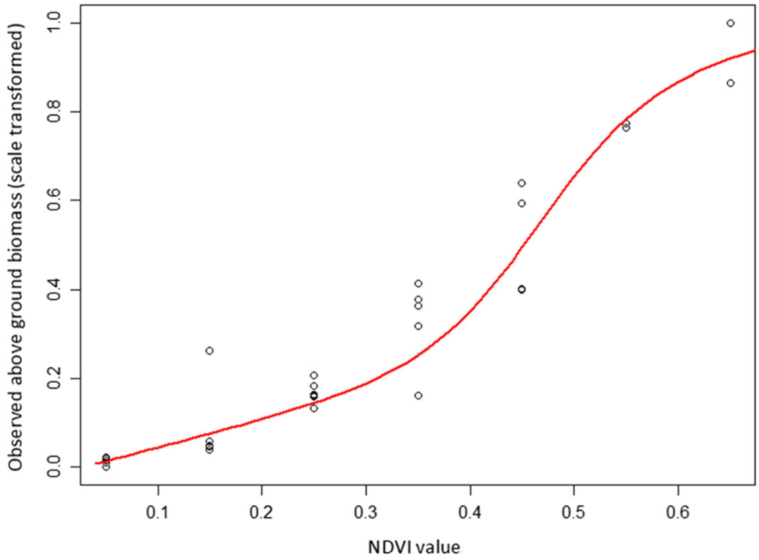

Fig. 7 Relationship of plot wise NDVI values with field estimated AGB as per ANN

the impacts of atmospheric elements, soil condition, site and situation, plant phenology, species association and diversity, natural and quasi-natural disturbances etc. occurring from local through regional to global scales (Huete and Liu 1994; Gao et al. 2013). Moreover, sensor characteristics play a pivotal role in derivation of these sorts of indices (Yoshioka et al. 2012). Possible sources of errors can also be from misclassification of pixels, faulty ground truthing, and scales of representation (Lu et al. 2014). Hence, sufficient precautions should be taken and externalities should be considered while assigning these indices as inputs in any model.

Although this study has used NDVI as a predictor or explanatory variable, there is always a scope of using any other vegetation index derived from hyper-spectral geospatial sources to compare for possible better outputs in ANN. The only criterion for becoming a better predictor variable is that it should possess greater correlation with the output layer of ANN in reality, i.e. AGB in the present context. Even, modifying the architecture of ANN by changing the number of input nodes, hidden layers, and node combinations can lead to better predictive capacity (Lippmann 1987). It was also realized from the study that application of multiple predictors (viz.

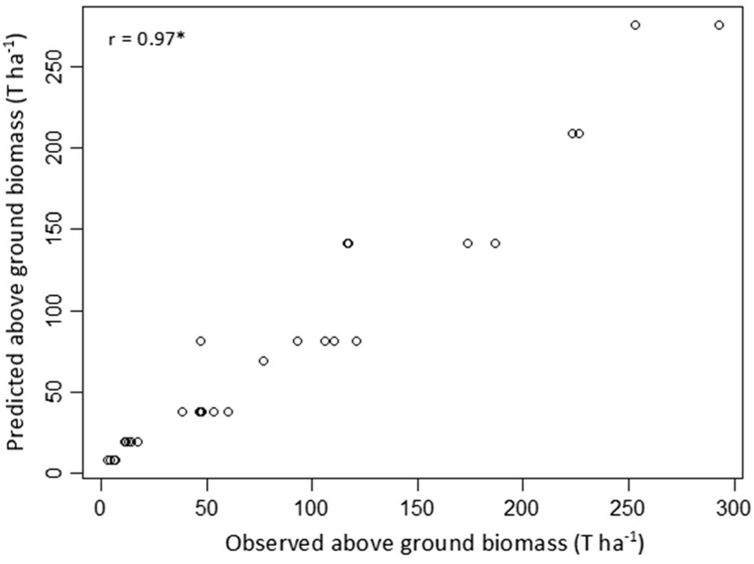

Fig. 8 Correlation between observed and ANN predicted biomass (* indicates statistical significance at $p < 0.01$)

different remote sensing based indices) as input nodes can enhance the certainty and effectiveness of the models. The problem of co-linearity does not impart any notable change in the outcomes of ANN unlike other traditional linear and nonlinear models. And it is one of the prime reasons of popularity of ANN over the traditional statistical methods among the scientific community (Liu et al. 2010).

Conclusion

This study inferred the capacity of artificial intelligence like ANN to establish a model to predict forest AGB from space-borne image NDVI values with greater precision. It compared ANN with few conventional linear and non-linear models. Being a pilot scale research, this study also indicated the pros and cons of using ANN. In reality, the ANN requires a large amount of input data for precision in model building in comparison to traditional models. The only 31 sites in this study might not be enough for this purpose and more number of sites should certainly enhance the analyzing potential of the model. Furthermore, incorporation of LiDAR data can significantly improve the output quality in ANN. Since, the primary objective of this pilot study was to develop a satisfactory model of minimum cost for AGB estimation that can be used with minimum infrastructure and technical difficulty by the ordinary forest officials and researchers, application of LiDAR data were intentionally avoided. After critically examining all the existing techno-economic infrastructure of the study region, the NDVI-based ANN model developed here can be considered as an effective one for satisfactory estimation of AGB in real-time applications.

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