Advanced Remote Sensing

http://publish.mersin.edu.tr/index.php/arsej

e-ISSN 2979-9104

Characterizing and estimating forest structure using active remote sensing: An overview

Elaheh Zadbagher *[1], **Aycan Murat Marangoz** [1], **Kazimierz Becek** [2]

[1] *Zonguldak Bulent Ecevit University, Geomatics Engineering Department, Türkiye, elaheza@yahoo.com, aycanmarangoz@beun.edu.tr*
[2] *Wroclaw University of Science and Technology, Faculty of Geoengineering, Mining, and Geology, Poland, kzimierz.becek@pwr.edu.pl*

Cite this study: Zadbagher, E., Marangoz, A. M., & Becek, K. (2023). Characterizing and estimating forest structure using active remote sensing: An overview. Advanced Remote Sensing, 3(1), 38-46

Keywords
Forest structure
RADAR
LiDAR
Biomass
Machine learning

Review Article
Received: 20.12.2022
Revised: 15.02.2023
Accepted: 11.03.2023
Published: 16.03.2023

check for updates

Abstract

Vegetation plays an important role in supporting our lives by maintaining many environmental and ecological services. Forests, as part of the vegetation cover, are the most critical components of the Earth's carbon cycle. The information about the forest structure is vital for ecosystem health, carbon cycle assessment, and a better understanding of the forest resources. Forest structural parameters estimation by field-based methods has limitations, such as being expensive, impractical, labor-intensive, and time-consuming at a large scale. Remote sensing has proven to be a more competent and low-cost tool for monitoring and measuring forest parameters compared to field surveys. Active remote sensing systems i.e., Light Detection and Ranging (LiDAR) and Radio Detection and Ranging (RADAR) provide horizontal and vertical forest structure information. In addition, these systems are susceptible to the forest components arrangement, given their ability to penetrate the different depths of the canopy. Therefore, there are many types of research focusing on the estimating of the forest aboveground biomass (AGB) which is one of the critical measures of forest resources, using active remote sensing. This research investigates the potential of active remotely sensed data to estimate forest structural parameters and extract data information. Furthermore, this research focused on various methods used for AGB estimation with active remote sensing.

1. Introduction

Forest ecosystems are usually defined by some characteristics including composition, structure and function. Forest functional attributes refer to issues such as rates and types of processes like carbon sequestration. Forest composition is defined by all plant species found in a stand or relative indexes of biodiversity. Forest structure can be described as the physical and temporal distribution of vegetation and trees in a forest. Because forest structure affects the carbon cycle, nutrient cycling and the availability of niches for various species, it can affect biodiversity and a variety of ecosystem processes. Hence, in the management of forest ecosystems and in reducing greenhouse gas emissions from forest degradation and deforestation forest structure is an important factor [1, 2].

Forest structure contains a set of indicators including vertical and horizontal distribution of layers (including the shrubs, trees, and ground cover) in a forest, species distribution, age, size, or combinations of them [3]. The horizontal structure consists of the diameter size distribution of individual or group tree species. The vertical structure is the most complex of all vegetation parameters that involve its differentiation into layers between the canopy and the ground. The forest's vertical structure reflects the distribution of different species relative to each other and the spatial distribution of tree individuals in the forest, which concerns many disciplines [4]. It also has important effects on the land surface process and constrains the accuracy of inference of forest characteristic parameters.

From early forest classification mapping to forest parameters retrieval forestry remote sensing has been developed with the development of remote sensing technology [5]. Forest studies by remote sensing started with local-scale forest mapping from aerial photography in the first half of the twentieth century. Since the launch of the first satellite sensor in 1972, remote sensing has provided increasing information on the structure of forested ecosystems and enabled forest studies on a large and global scale. Also, with the development of LiDAR and Synthetic Aperture RADAR (SAR) technologies, advances in data analysis techniques and ecosystem modeling, their combination has provided an important role for remote sensing in forestry applications. Remote sensing has been used to identify, detect, classify, evaluate and measure many forest parameters such as tree height, Diameter at Breast Height (DBH), biomass, carbon, basal area, total leaf area, tree density and forest cover types [1, 3, 5]. Furthermore, to overcome some of the limitations of terrestrial surveys, combining field measurements with spaceborne and airborne remotely sensed data is used to obtain the necessary information on forest structure. Depending on the required level of detail of the output information and the specific application, various remote sensing data sources can be applied including optical data, LiDAR and RADAR data. Each of these data sources has proven to have advantages and potential for forestry applications. Active remote sensing systems like RADAR and LiDAR are considered the most valuable tools to provide volumetric forest and vertical structure measures because it is sensitive to the arrangement of forest components and it can penetrate to the different depths of the canopy. They have been successfully used to estimate Parameters of forest structure such as AGB [6-8], forest canopy height [2, 9, 10], leaf area index, canopy gap size and clumping index [5].

2. An overview of RADAR systems

RADAR systems are active sensors that provide their electromagnetic energy source. Active RADAR sensors, whether spaceborne or airborne, operate in an electromagnetic spectrum range of 1 mm–1 m. Moreover, Radar systems take advantage of the ability to penetrate through clouds and other media such as vegetation canopy due to the atmospheric permeability and much longer wavelengths in this region of the electromagnetic spectrum. Thus, these systems provide day/night, all-weather capability, and as well as sub-surface information dependent on wavelength. Microwave spectrum bands often used for remote sensing include P-band, L-band, S-band, C-band and X-band. RaDAR systems transmit energy to the ground and record the backscattered signals from the target to the radar antenna producing an image at microwave wavelengths. The backscatter of the RADAR signal is driven by the target properties and the system characteristics. The RADAR parameters include 1) frequency or wavelength; 2) Polarization refers to the orientation of the electrical field of the electromagnetic wave and 3) Incidence angle refers to the angle between the Earth's surface plane and the direction of illumination of the RADAR. The target or surface parameters include 1) Dielectric properties; 2) Surface roughness; 3) Structure and orientation of objects on the surface. The RADAR signal is mainly sensitive to the structure of the surface. A surface will appear rough (bright) or smooth (dark), according to the scale of the variations of the surface concerning wavelength [11].

The depth of penetration of microwave radiation into vegetation depends on the frequency, dielectric properties, size, and geometry of the interacting vegetation parts. Therefore, microwave observations from different frequencies include information from different parts of the vegetation [12]. With increasing wavelength and decreasing frequency, the penetration capability of the transmitted signals increases. Considering forests (Figure 1), the RADAR signal in longer wavelengths such as L-band is backscattered at tree trunks, big branches and the ground, while the signal in shorter wavelengths such as X-band is backscattered at leaves and small branches [13]. Thus, the wavelength used determines the size of the scatterers that the sensor is sensitive to. As shown in Figure 1, X-band has a short wavelength with limited penetrating ability, while L-band and P-band have a longer wavelength signal with higher penetrating ability. C-band is considered a good compromise between X- and L-band.

The invention of the SAR technique in the early 1950s was an important step in the development of RADAR remote sensing. SAR is a coherent side-looking RADAR system that uses the platform's flight path to electronically simulate an extremely large antenna or aperture and produces high-resolution images. Therefore, greatly increasing the RADAR resolution was the main advantage of the SAR technique. The ideal remote sensing application of RADAR needs an remote sensing system that provides precise and high-resolution, geo-referenced data about Earth's surface [14]. Based on the combination of polarization modes and frequency bands used in data acquisition, SAR can be categorized as single polarization, multiple polarization, single frequency, and multiple frequencies [15].

The breakthrough in the development of active remote sensing occurred in 1970 with a technique called SAR interferometry (InSAR). The fundamental idea of InSAR is to combine scattering signals obtained at a different time (along-track interferometry) or from a different location (cross-track interferometry). While SAR images only provide the 2D coordinates of the scatterers, InSAR provides the measurement of the 3D coordinates of a target at the Earth's surface. In other words, a satellite SAR can observe the same area from slightly different look angles.

This can be done simultaneously from different orbits (with two RADARs mounted on the same platform) or at different times from the same orbit but utilizing repetitive acquisitions [11]. InSAR technique is widely applied in many fields like forest management, monitoring of surface deformation, polar surveys, monitoring glacial movement and ocean current, and hydrological studies [16]. In addition, it has been used in forestry to classify and estimate forest-related variables such as tree height, basal area, trunk volume and biomass. InSAR also is a potential technique to generate Digital Elevation Model (DEM), widely used in the geoscientific community, utilizing the phase component of complex RADAR signals. An appropriately equipped spaceborne InSAR system can be used to generate a highly accurate global DEM at a significantly lower cost and significantly less time than other systems. SRTM and TanDEM-X are examples of freely InSAR satellite missions that have acquired data over the world forests.

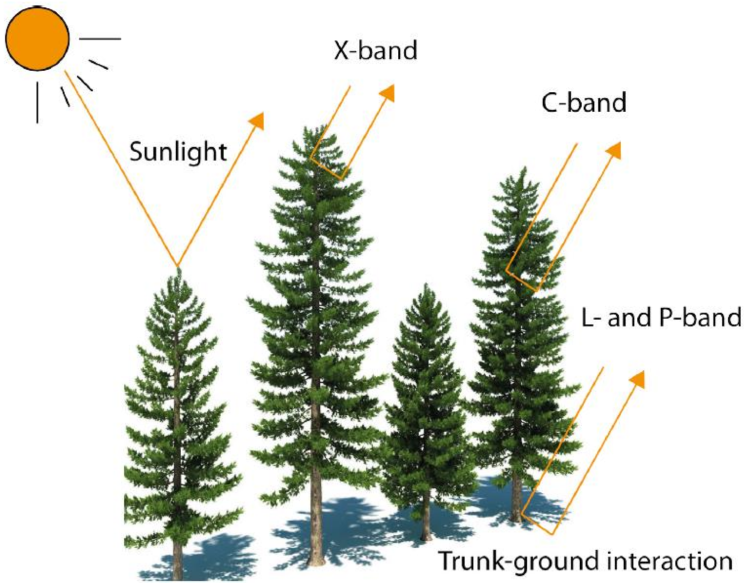

Figure 1. Illustration of penetration in a forest canopy with RADAR frequency bands [11]

3. An overview of LiDAR systems

LiDAR is an active remote sensing system where ranges to the Earth are measured by light in the form of a pulsed laser. Reflected light energy from the object that backs to the LiDAR sensor is recorded. The reflection time, taken for emitted light to travel to the ground and return, is measured. To measure the distance to an object, LiDAR instruments utilize the time-of-flight measurement principle. The 3D position of an object is described by the precise orientation of the distance measurements between the sensor and a reflective object, and the known sensor position. The LiDAR instrument principally consists of 1) A LiDAR sensor that scans the ground from side to side with a pulsed laser beam, 2) GPS that identifies the altitude and location of the light energy 3) Inertial measurement units (IMU) that tracks the orientation and speed of the platform in the sky and 4) Computer that records all of the height information while the LiDAR scans the surface.

There are three types of LiDAR systems including terrestrial, airborne and spaceborne according to the platform. However, airborne and terrestrial LiDAR systems are only useful to small extents because of the high acquisition costs and limited coverage. In contrast, a spaceborne system is an ideal option for large and global-scale studies [17]. LiDAR systems use near-infrared (NIR), visible, or ultraviolet to sense objects. These optical sensors typically use the NIR region of the electromagnetic spectrum to get the distance [15].

The advantage of LiDAR measurements is that they are relatively direct measurements of or as a function of height. This is an interesting proposition for remote sensing of vegetation cover as vegetation height is an important biophysical feature that provides information about observed vegetation. There are two major types of LiDAR systems used for forestry applications including full waveform and discrete return. They differ from each other in how they sample the three-dimensional structure of a canopy horizontally and vertically. Horizontal sampling is defined by the footprint area and the number of these footprints per unit area. Vertical sampling refers to the number of range samples recorded for each emitted pulse.

Discrete return systems record discrete points for each peak location in the waveform curve. These individual or discrete points are known as returns. Discrete return systems can typically record a few, typically four, multiple returns from each pulse during flight. Contrarily, full waveform systems record the distribution of returned energy by sampling it at fixed time intervals. The number of recording intervals determines the amount of detail contained in a laser footprint. Full waveform systems are more complex to process, but can generally capture more information compared to discrete return systems. For forested areas, the result is a waveform that represents the forest structure from the top of the canopy to the ground surface [18, 19].

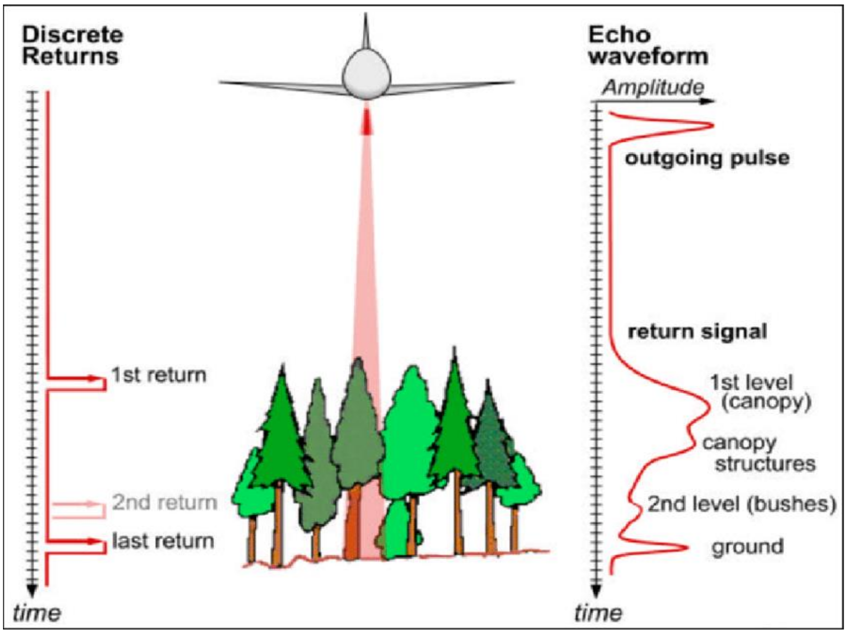

Figure 2. Differences between full waveform and discrete return [19]

One or many returns can be produced when a laser pulse hits the canopy of the forest. Because there are gaps in the forest canopy and the canopy is not a solid surface, the situation becomes more complicated when a laser pulse passes the canopy top and before reaching the ground it interacts with different parts of the canopy like the leaves, trunk and branches. This sequence of events can cause multiple returns to be recorded for a single laser pulse. Some systems also record the full waveform of the laser pulse's reflected. It is assumed that the first returns come mainly from the canopy top and the last returns from the ground, which is significant to extract the terrain model [20].

4. Active remote sensing of forest structure

LiDAR devices make it easy to collect detailed information that accurately captures the 3D structure of the earth's surface, while RADAR data allows for overcoming the common atmospheric and shadow effects that often occur in forested areas [1, 13]. LiDAR is a unique technology for characterizing forest structures at different scales. LiDAR data have been used to obtain high-resolution elevation data and to estimate vertical forest structure, AGB, canopy height and leaf area index [17]. Although LiDAR-derived height often underestimates the actual height due to system configuration and gaps in the canopy, the accuracy obtained is higher than that of other sensors [13]. LiDAR can provide both vertical and horizontal information with vertical and horizontal sampling. Sampling quality depends on the used type of LiDAR system and whether it is a full-waveform or discrete return system.

There are two main approaches namely area-based methods and single tree-based methods for retrieving forest structural characteristics from LiDAR data. This method allows obtaining canopy height information via relatively coarse-resolution satellite or airborne LiDAR data. In area-based methods, the nonphysical distribution-related attributes of LiDAR height measurements and statistical metrics are extracted from the laser point clouds. They are then used to estimate forest characteristics like basal area, mean tree height, volume and AGB at stand and plot level. Single tree-based methods focus on the recognition of individual trees. In this method, the tree attributes like the height of a tree, species information and crown dimensions are measured [1]. The resulting features can be used to derive other features like standing volume and AGB through various modeling techniques.

SAR remote sensing is sensitive to the scatterer's geometry, structure, and dielectric properties. In addition, SAR signals can give better information about the vertical structure as they can penetrate deeper into the vegetation layers depending on the wavelength. Therefore, there are many studies on the extraction of vegetation height utilizing these data. For instance, SAR techniques such as InSAR or PolInSAR can estimate the canopy height of vegetation, which is an important variable for biomass estimation [13]. It has been shown to enhance biomass estimation of predicted vertical structure, including ground volume ratio, forest height, and volume and ground polarimetric scattering attributes. Space-borne sensors that obtain potential use data for forest structural mapping either generate data on sparse forest canopy samples or offer continuous mapping capabilities. The Geoscience Laser Altimeter System (GLAS) sensor on the lCESat (Ice, Cloud and land Elevation Satellite) is an example of the first category. Later, ICESat-2 launched in 2018 and has since collected continuous elevation data over the Earth's surface. Another category is RADAR sensors with interferometry capability. They have been utilized to create continuous height maps of the canopy surface or some intermediate level between the ground level and the canopy surface.

Akay et al. [21] analyzed the structural characteristics of a forest, including canopy closure, crown diameter, vegetation density and mean tree height using airborne LiDAR data. The LiDAR-derived measurements of crown diameter and mean tree height were compared with field-based measurements. Their analysis revealed that the mean tree height, vegetation density, canopy closure and total crown width were 74.72 m, 26.05%, 71.15% and 16.82 m, respectively. They also showed significant differences between field measurements and LiDAR-derived crown width and tree height values. The results of this study demonstrated that for relatively large study areas the structural features of forest areas can be determined more quickly, accurately and inexpensively using LiDAR-based and GIS techniques. Brigot et al. [22] predicted forest vertical structure parameters using LiDAR and L-band PolInSAR data in a forest in Québec, Canada. They considered the influence of acquisition parameters like ground elevation, local surface slope, and interferometric baseline, along with parameters defining the coherence shape. They focused on three descriptors of canopy including canopy height profile class and canopy height and cover. They used a computer model to correlate PolInSAR features to canopy cover and canopy height; they then utilized a random forest model to a vertical distribution class. The vertical profile was divided into three separate classes with an accuracy of 66%. They showed that the predicted parameters from this study may improve estimates of AGB stock. Many studies have demonstrated the derivation of the vertical structure of forests using various methods and data sources, including LiDAR, SAR, InSAR, and a combination thereof [9, 13, 20, 23-25].

5. AGB estimation

Generally, field-based measurements and remotely sensed techniques are used to estimate AGB. Field-based methods provide the most accurate AGB values but have limitations, such as being expensive, impractical, labour-intensive, and time-consuming at a large scale [26]. In addition, tropical forests usually contain obstacles to field-based tree height estimation, including tall canopies, dense understory vegetation, and closed-canopy conditions [27]. In these conditions, remote sensing has proven to be a more competent tool for monitoring and measuring forest biomass at various scales. Different remote sensing data types can be used for forest AGB estimation, including optical and active sensors data, i.e., LiDAR and SAR. Active remote sensing systems can penetrate the vegetation canopy. Hence, they have great potential for monitoring and assessment of AGB.

In general, two general methods, i.e., reflectance-biomass models and forest height-biomass models, can be identified for mapping biomass using Earth observation satellites data. The reflectance biomass models concern the direct relationship between image reflection or backscattering and biomass. In the forest height-biomass models, forest height is utilized as the main predictor for estimating biomass. It is well known that the energy is reflected in optical sensors, while it is backscattered in RADAR sensors. The ratio of returned energy is determined by physical or geometry parameters like canopy structure, water contents, dielectric properties, and leaf pigment. Backscatter or reflectance varies depending on wavelength. The short wavelengths of optical sensors respond to small components of a canopy, like twigs and leaves. They cannot penetrate deep into the canopy. They generally carry a signal not on canopy height or biomass, but on the percent cover of canopies. Therefore, biomass estimation models based on reflected energy measured utilizing optical remote sensing tend to saturate at very low biomass levels [9].

Unlike optical sensors, active RADAR sensors are not affected by cloud cover or weather conditions and hence are useful tools for mapping forest biomass. In this point, backscatter amplitude information acquired using different RADAR bands or various polarizations is correlated with forest biomass because of the physical relationship between backscatter and the volumetric density of canopy elements. RADAR sensors with shorter wavelengths, such as X and C bands are sensitive to the canopy's small components. RADAR sensors with longer wavelengths such as L-band and P-band react to larger forest components, like stems and branches. According to the literature, RADAR backscatter saturates at certain biomass levels depending on the wavelength. Hence, due to weak sensitivity to higher levels of biomass, reflectance-biomass models are inadequate to cover the full range of biomass values [28].

Biomass also can be estimated from tree density and tree volume models. Since the woody density of trees is not highly variable among different species of a specific ecoregion, volume estimates can easily be converted to biomass. The volume of an individual tree can simply be considered as the product of tree height and tree DBH. Therefore, the biomass of a plot depends on the number of trees, their height and DBH. In closed canopies, there is a very close relationship between volume, canopy height, and biomass during a large part of the trees' growth stage [29]. Furthermore, Solberg et al. [30] estimated forest biomass with an RMSE value of 43% using remotely sensed height as the only predictor. Therefore, theoretically measuring the forest canopy height provides a very useful biomass predictor. Forest height, as the major predictor of forest biomass, can be extracted to a certain extent using 3D remote sensing and then used to estimate biomass or wood volume. In terms of modeling methods used in AGB estimation, non-parametric modeling categories are frequently used.

5.1. Machine learning for estimating AGB

Allometric models are widely used to build AGB models, but they cannot completely capture the complex heterogeneous landscapes in which multiple environmental variables impact the spatial distribution of AGB [31]. There are many different prediction models other than allometric models to measure AGB, including spatial statistical and machine learning (ML) models. With advances in the modeling of non-linear systems and the development of computer science techniques, ML methods have become widespread. ML is an artificial intelligence application trained by experience without any programming. ML approaches are powerful regression techniques to solve complex and non-linear problems. Furthermore, ML algorithms are not dependent on data distribution. Thus, it can seamlessly integrate data from different sources [32]. ML algorithms are an alternative to parametric methods in cases where the data is heterogeneous and does not show normality, such as in tropical forests [8]. Due to the complex relationships for AGB prediction, nonparametric ML approaches represent potentially helpful methods to predict AGB [33]. A wide variety of ML algorithms have been used to predict AGB already, including random forest (RF) [7, 26, 32], artificial neural network (ANN) [34, 35], maximum entropy (MaxEnt) [28, 33], Gaussian process (GP) [36], multivariate adaptive regression splines (MARS) [33, 37], K-nearest neighbor (KNN) [38, 39] and support vector machine (SVM) [31, 34, 40].

Besides, selecting suitable variables from satellite data and physical variables is essential to model the AGB. Some studies have used various variables such as vegetation indices, texture indices, multispectral bands, LiDAR metrics, topographic variables or a combination of these to estimate AGB by ML algorithms. For instance, Ghosh and Behera [32], in a study conducted in a tropical forest in India, considered SAR, texture and vegetation indices to estimate AGB. Chen et al. [34] used texture characteristics, vegetation indices, multispectral bands and vegetation biophysical variables to estimate biomass through ML algorithms. They found that vegetation biophysical variables and texture characteristics were the most critical variables as predictors. Dang et al. [41] applied a combination of 11 spectral and texture variables to estimate the AGB of Yok Don National Park in Vietnam. In a study, Kappas [26] considered 52 variables, including vegetation indices, spectral bands, topography and textures, to predict forest AGB using the RF algorithm. They found that a combination of topography, vegetation indices and spectral variables present the highest prediction. In another study, multispectral reflectance, vegetation indices, vegetation biophysical, topographical indicators and texture variables were used as predictors for the AGB estimation. The results demonstrated that multispectral variables were primary and topographic variables were more important than texture features in complex AGB modeling [42]. LiDAR-derived metrics to estimate AGB in tropical forest areas by Marchesan et al. [8] and Rex et al. [38].

Mangla et al. [7] applied LiDAR and fully polarimetric SAR data to estimate forest AGB using the RF algorithm. Zhang et al. [33] evaluated eight ML algorithms for AGB estimation using tree cover data, canopy height, leaf area index, net primary production, and climatic and topographical data. They utilized five tree-based ensemble algorithms including RF, extremely randomized trees (ERT), gradient boosted regression tree (GBRT), stochastic gradient boosting (SGB), and categorical boosting (CatBoost); and used three nonensemble algorithms including multivariate adaptive regression splines (MARS), SVM, and ANN. The results of the study showed that tree-based models have better performances than nonensemble models and the CatBoost model outperformed the other models. Jiang et al. [43] generated the forest canopy height map to estimate AGB in Northern China using a stacking algorithm by synergizing ICESat-2 with Sentinel-1. The algorithm consisted of SVM, multiple linear regression (MLR), RF, and k-nearest neighbor (KNN). They showed that stacking provides the best estimation accuracy for the forest canopy height and compared with SVM, MLR, RF, and kNN RMSE obtained by stacking algorithm decreased by 24.9%, 25.2%, 18.7%, and 22.8%, respectively. The most utilized nonparametric methods include ANN, RF, and SVM, among others and have been used in many studies to estimate biomass by integrating remote sensing and field data [35, 38, 41, 42, 44, 45].

RF, ANN, and SVM models are ensemble algorithms that can be utilized for both classification and regression problems. RF assembles decision trees on various subsets of the relevant dataset. Each tree depends on the values of a random vector sampled independently and with the same distribution. At each node of the tree, the split is determined by randomly choosing a set of predictor variables. In the regression trees, the significance of each node is determined by employing input data to evaluate which variable in that node ideally characterizes the remaining observations. The performance of the RF model is significantly affected by the number of trees [32]. ANN is made up of a layered structure, including an input layer, one or more hidden layers, and an output layer. Numerous hidden layers can be applied to build a more complex model to fit a challenging problem. The performance of the ANN model depends on connection weights between layers [42]. SVM is a kernel-based algorithm that transforms low-dimensional data into a higher-dimensional one utilizing a non-linear kernel function to minimize model complexity and training error. SVM models can achieve high accuracies, even when training data are small [33].

6. Conclusion

Active remote sensing is considered an important tool to provide volumetric and vertical structure forest measures because it is sensitive to the arrangement of forest components and it can penetrate to the different depths of the canopy. Structural information extraction and AGB estimation can be improved by combining RADAR and LiDAR data. Application in large areas is the main advantage of the integration of RADAR and LiDAR. In order to estimate forest AGB different methods of prediction can be used. Non-parametric models are most widely used to estimate forest AGB. Parametric models like multiple regression and linear regression, have been replaced by non-parametric models having a high ability to capture forest AGB's heterogeneity. In comparison to parametric algorithms, nonparametric approaches are more flexible, create more complex models and represent potentially helpful methods to estimate AGB. In addition, among the various non-parametric ML models, ANN, SVM, and RF models have the most used because of their highly accurate forest AGB estimating ability.

Funding

This research received no external funding.

Author contributions

Elaheh Zadbagher: Conceptualization, Investigation, Visualization, Writing-original draft. **Aycan Murat Marangoz:** Conceptualization, Supervision, Writing-review and editing. **Kazimierz Becek:** Conceptualization, Supervision, Writing-review and editing.

Conflicts of interest

The authors declare no conflicts of interest.

References

1. Latifi, H. (2012). Characterizing forest structure by means of remote sensing: a review. *Remote Sensing-Advanced Techniques and Platforms*, 1-26.
2. García, M., Saatchi, S., Ustin, S., & Balzter, H. (2018). Modelling forest canopy height by integrating airborne LiDAR samples with satellite Radar and multispectral imagery. *International journal of applied earth observation and geoinformation*, *66*, 159-173.
3. Bispo, P. D. C., Dos Santos, J. R., Valeriano, M. D. M., Graça, P. M. L. D. A., Balzter, H., França, H., & Bispo, P. D. C. (2016). Predictive models of primary tropical forest structure from geomorphometric variables based on SRTM in the Tapajós region, Brazilian Amazon. *PloS one*, *11*(4), e0152009.
4. Haidari, M., Namiranian, M., Gahramani, L., Zobeiri, M., & Shabanian, N. (2013). Study of vertical and horizontal forest structure in Northern Zagros Forest (Case study: West of Iran, Oak forest). *Eurepean Journal of Experimental Biol*ogy, *3*(1), 268-278.
5. Zhao, J., Li, J., & Liu, Q. (2013). Review of forest vertical structure parameter inversion based on remote sensing technology. *Journal of Remote Sensing*, *17*, 697-716.
6. Neumann, M., Saatchi, S. S., Ulander, L. M., & Fransson, J. E. (2012). Assessing performance of L-and P-band polarimetric interferometric SAR data in estimating boreal forest above-ground biomass. *IEEE Transactions on Geoscience and Remote Sensing*, *50*(3), 714-726.
7. Mangla, R., Kumar, S., & Nandy, S. (2016, May). Random forest regression modelling for forest aboveground biomass estimation using RISAT-1 PolSAR and terrestrial LiDAR data. In *Lidar Remote Sensing for Environmental Monitoring XV* (Vol. 9879, pp. 109-119). SPIE.
8. Marchesan, J., Alba, E., Schuh, M. S., Favarin, J. A. S., & Pereira, R. S. (2020). Aboveground biomass estimation in a tropical forest with selective logging using random forest and Lidar data. *Floresta*, *50*(4), 1873-1882.
9. Sadeghi, Y., St-Onge, B., Leblon, B., & Simard, M. (2016). Canopy height model (CHM) derived from a TanDEM-X InSAR DSM and an airborne lidar DTM in boreal forest. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *9*(1), 381-397.
10. Berninger, A., Lohberger, S., Zhang, D., & Siegert, F. (2019). Canopy height and above-ground biomass retrieval in tropical forests using multi-pass X-and C-band Pol-InSAR data. *Remote Sensing*, *11*(18), 2105.
11. Persson, H. (2014). *Estimation of forest parameters using 3D satellite data* (Vol. 2014, No. 2014: 84).
12. Teubner, I. E., Forkel, M., Jung, M., Liu, Y. Y., Miralles, D. G., Parinussa, R., ... & Dorigo, W. A. (2018). Assessing the relationship between microwave vegetation optical depth and gross primary production. *International journal of applied earth observation and geoinformation*, *65*, 79-91.

13. Schlund, M., & Davidson, M. W. (2018). Aboveground forest biomass estimation combining L-and P-band SAR acquisitions. *Remote Sensing*, *10*(7), 1151.
14. Becek, K. (2010). Biomass representation in synthetic aperture radar interferometry data sets. Saechsische Landesbibliothek-Staats-und Universitaetsbibliothek Dresden
15. Zhu, L., Suomalainen, J., Liu, J., Hyyppä, J., Kaartinen, H., & Haggren, H. (2018). A review: Remote sensing sensors. *Multi-purposeful application of geospatial data*, 19-42.
16. Zou, W., Li, Y., Li, Z., & Ding, X. (2009). Improvement of the accuracy of InSAR image co-registration based on tie points–a review. *Sensors*, *9*(02), 1259-1281.
17. Nie, S., Wang, C., Xi, X., Luo, S., Li, G., Tian, J., & Wang, H. (2018). Estimating the vegetation canopy height using micro-pulse photon-counting LiDAR data. *Optics express*, *26*(10), A520-A540.
18. Huang, S., Hager, S. A., Halligan, K. Q., Fairweather, I. S., Swanson, A. K., & Crabtree, R. L. (2009). A comparison of individual tree and forest plot height derived from lidar and InSAR. *Photogrammetric Engineering & Remote Sensing*, *75*(2), 159-167.
19. Lim, K., Treitz, P., Wulder, M., St-Onge, B., & Flood, M. (2003). LiDAR remote sensing of forest structure. *Progress in physical geography*, *27*(1), 88-106.
20. Kaasalainen, S., Holopainen, M., Karjalainen, M., Vastaranta, M., Kankare, V., Karila, K., & Osmanoglu, B. (2015). Combining lidar and synthetic aperture radar data to estimate forest biomass: status and prospects. *Forests*, *6*(1), 252-270.
21. Akay, A. E., Wing, M. G., & Sessions, J. (2012). Estimating structural properties of riparian forests with airborne lidar data. *International Journal of Remote Sensing*, *33*(22), 7010-7023.
22. Brigot, G., Simard, M., Colin-Koeniguer, E., & Boulch, A. (2019). Retrieval of forest vertical structure from PolInSAR data by machine learning using LIDAR-derived features. *Remote Sensing*, *11*(4), 381.
23. Jin, S., Su, Y., Gao, S., Hu, T., Liu, J., & Guo, Q. (2018). The transferability of Random Forest in canopy height estimation from multi-source remote sensing data. *Remote Sensing*, *10*(8), 1183.
24. Fagua, J. C., Jantz, P., Rodriguez-Buritica, S., Duncanson, L., & Goetz, S. J. (2019). Integrating LiDAR, multispectral and SAR data to estimate and map canopy height in tropical forests. *Remote Sensing*, *11*(22), 2697.
25. Pourshamsi, M., Xia, J., Yokoya, N., Garcia, M., Lavalle, M., Pottier, E., & Balzter, H. (2021). Tropical forest canopy height estimation from combined polarimetric SAR and LiDAR using machine-learning. *ISPRS Journal of Photogrammetry and Remote Sensing*, *172*, 79-94.
26. Nguyen, T. D., & Kappas, M. (2020). Estimating the aboveground biomass of an evergreen broadleaf forest in Xuan Lien Nature Reserve, Thanh Hoa, Vietnam, using SPOT-6 data and the random forest algorithm. *International Journal of Forestry Research*, *2020*, 1-13.
27. Hunter, M. O., Keller, M., Victoria, D., & Morton, D. C. (2013). Tree height and tropical forest biomass estimation. *Biogeosciences*, *10*(12), 8385-8399.
28. Saatchi, S. S., Harris, N. L., Brown, S., Lefsky, M., Mitchard, E. T., Salas, W., ... & Morel, A. (2011). Benchmark map of forest carbon stocks in tropical regions across three continents. *Proceedings of the national academy of sciences*, *108*(24), 9899-9904.
29. St-Onge, B., Hu, Y., & Vega, C. (2008). Mapping the height and above-ground biomass of a mixed forest using lidar and stereo Ikonos images. *International Journal of Remote Sensing*, *29*(5), 1277-1294.
30. Solberg, S., Næsset, E., Gobakken, T., & Bollandsås, O. M. (2014). Forest biomass change estimated from height change in interferometric SAR height models. *Carbon Balance and Management*, *9*, 1-12.
31. Dai, S., Zheng, X., Gao, L., Xu, C., Zuo, S., Chen, Q., ... & Ren, Y. (2021). Improving plot-level model of forest biomass: A combined approach using machine learning with spatial statistics. *Forests*, *12*(12), 1663.
32. Ghosh, S. M., & Behera, M. D. (2018). Aboveground biomass estimation using multi-sensor data synergy and machine learning algorithms in a dense tropical forest. *Applied Geography*, *96*, 29-40.
33. Zhang, Y., Ma, J., Liang, S., Li, X., & Li, M. (2020). An evaluation of eight machine learning regression algorithms for forest aboveground biomass estimation from multiple satellite data products. *Remote Sensing*, *12*(24), 4015.
34. Chen, L., Ren, C., Zhang, B., Wang, Z., & Xi, Y. (2018). Estimation of forest above-ground biomass by geographically weighted regression and machine learning with sentinel imagery. *Forests*, *9*(10), 582.
35. Santi, E., Paloscia, S., Pettinato, S., Cuozzo, G., Padovano, A., Notarnicola, C., & Albinet, C. (2020). Machine-learning applications for the retrieval of forest biomass from airborne P-band SAR data. *Remote Sensing*, *12*(5), 804.
36. Vafaei, S., Soosani, J., Adeli, K., Fadaei, H., Naghavi, H., Pham, T. D., & Tien Bui, D. (2018). Improving accuracy estimation of Forest Aboveground Biomass based on incorporation of ALOS-2 PALSAR-2 and Sentinel-2A imagery and machine learning: A case study of the Hyrcanian forest area (Iran). *Remote Sensing*, *10*(2), 172.
37. Baloloy, A. B., Blanco, A. C., Candido, C. G., Argamosa, R. J. L., Dumalag, J. B. L. C., Dimapilis, L. L. C., & Paringit, E. C. (2018). Estimation of mangrove forest aboveground biomass using multispectral bands, vegetation indices and biophysical variables derived from optical satellite imageries: Rapideye, planetscope and sentinel-2. *ISPRS annals of the photogrammetry, remote sensing and spatial information sciences*, *4*, 29-36.

38. Rex, F. E., Silva, C. A., Dalla Corte, A. P., Klauberg, C., Mohan, M., Cardil, A., ... & Hudak, A. T. (2020). Comparison of statistical modelling approaches for estimating tropical forest aboveground biomass stock and reporting their changes in low-intensity logging areas using multi-temporal LiDAR data. *Remote Sensing*, *12*(9), 1498.
39. Zhang, W., Zhao, L., Li, Y., Shi, J., Yan, M., & Ji, Y. (2022). Forest Above-Ground Biomass Inversion Using Optical and SAR Images Based on a Multi-Step Feature Optimized Inversion Model. *Remote Sensing*, *14*(7), 1608.
40. Gleason, C. J., & Im, J. (2012). Forest biomass estimation from airborne LiDAR data using machine learning approaches. *Remote Sensing of Environment*, *125*, 80-91.
41. Dang, A. T. N., Nandy, S., Srinet, R., Luong, N. V., Ghosh, S., & Kumar, A. S. (2019). Forest aboveground biomass estimation using machine learning regression algorithm in Yok Don National Park, Vietnam. *Ecological Informatics*, *50*, 24-32.
42. Chen, L., Wang, Y., Ren, C., Zhang, B., & Wang, Z. (2019). Optimal combination of predictors and algorithms for forest above-ground biomass mapping from Sentinel and SRTM data. *Remote Sensing*, *11*(4), 414.
43. Jiang, F., Zhao, F., Ma, K., Li, D., & Sun, H. (2021). Mapping the forest canopy height in Northern China by synergizing ICESat-2 with Sentinel-2 using a stacking algorithm. *Remote Sensing*, *13*(8), 1535.
44. López-Serrano, P. M., Cárdenas Domínguez, J. L., Corral-Rivas, J. J., Jiménez, E., López-Sánchez, C. A., & Vega-Nieva, D. J. (2019). Modeling of aboveground biomass with Landsat 8 OLI and machine learning in temperate forests. *Forests*, *11*(1), 11.
45. Su, H., Shen, W., Wang, J., Ali, A., & Li, M. (2020). Machine learning and geostatistical approaches for estimating aboveground biomass in Chinese subtropical forests. *Forest Ecosystems*, *7*, 1-20.