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Review Article

A review of forest biomass estimation and modeling methods by remote sensing

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ABSTRACT

Background and objective: Detailed evaluation of biomass using Remote Sensing and Geographic Information systems is very important to manage the forest and its role as a carbon source and climate change. Ground sensing data have made a big change in compiling and exploiting information about forest biomass, But non-local equations and the use of different radar and optical images, and also huge expenses have caused ambiguities in the accurate estimation of biomass. This study aims to investigate the capabilities of different remote sensing data for modeling and estimating forest biomass.
Materials and methods: Today, by using the conducted research and also by examining the conducted methods, it is possible to have an accurate assessment of biomass estimation, which brings the lowest cost and the highest efficiency. In this study, the challenges of the forest biome were investigated by reading numerous domestic and international articles and also with the opinion of natural resources experts in Iran.
Results and conclusion: After reviewing the opinions of experts, all the solutions and challenges of the existing methods for estimating and modeling the forest biomass, it was concluded that to increase the accuracy and reduce the costs, the use of remote sensing capabilities can be useful in the assessment of the forest biomass. Decision makers and managers, especially in the natural resources area, can use remote sensing capabilities to prevent crises and monitor forests.

1. Introduction

In recent years, the forest cover as an indicator of development has great significance. It plays an important role in establishing the ecological balance on Earth and is one of the most important and influential issues around the world. Forest biomass is an important criterion for ecosystem efficiency and has a significant potential for energy production and evaluation of available carbon for climate

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change modeling. Forests are necessary for balancing and moderating climatic change. Forests and trees play a major role in carbon capture and storage and in providing environmental services (FAO, 2016).

Accurate evaluation of biomass in order to forest management and understanding its role as a carbon source is very important. Half of the forest biomass consists of carbon. The forests store approximately 80% of the above-ground and 40% of below-ground carbon storage (Smithson, 2002). Atmospheric carbon is transformed into organic material by photosynthesis and returns again to the atmosphere by carbon dioxide-induced mechanisms involved. Biomass indicates the environmental health conditions of a forest ecosystem. Integrated geographical techniques, remote sensing, and (SAR), have the significant potential to map and understand the environmental processes of the forest (Sinha et al., 2015).

Accurate, true, and up-to-date information from forests provided by remote sensing and geographic information systems as well as modern methods in a very short time and at a very low cost, can effectively be resulted in enforcing the Kyoto Protocol of the United Nations Convention on Climate Change (Nichol & Sarker, 2010).

Given that the deforestation rate in the world is alarming, scientists have proven that biomass changes are important for evaluating the amount of deforestation and forestry processes. Estimations of forest biomass are recorded in terms of energy, however, uncontrolled biomass production can lead to deforestation, because burning trees for power can emit more carbon pollution than burning coal, and the industry causes long-lasting damage to forests and wildlife.

The biomass energy industry turns trees into wood pellets and then burns them for power at a utility-scale. Organic matters used to generate biomass energy include forest debris (shoots, dead trees), wood chips, tree cuttings, and municipal solid waste. This means that wood is the largest biomass energy source.

Due to the environmental, topography, and biophysical complexities of the forest ecosystems, global and transferable techniques for measuring carbon resources have not been developed so far, but remote sensing techniques have made them easy to access (Galidaki et al., 2017).

Although traditional classification methods such as the minimum distances and the maximum likelihood are known as effective methods for extracting coverage and land use information, there are also some constraints such as failed to use of features including texture, size scale, association with other classes, and the shape of pixels adjacent to the classification algorithm (Cleve et al., 2008).

The distinction between different classes using spectral properties is mostly difficult and creates noise in the image. To manage the problem and to increase the accuracy of the maps, spectral information can be combined with other side information such as image texture parameters, moisture maps, DEM, and other information. In addition, newer and more complete algorithms which combine spectral data with textural and conceptual data could be used to provide planners with better and more accurate maps in order to make better decisions (Cleve et al., 2008; Mokhtari et al., 2021; Zarei et al., 2021).

In experimental works, Nichol and Sarker (2010), Ghasemi et al. (2012), and Amini and Sumantyo, (2009) have indicated that a combination of optical and radar data and simultaneous use of them would provide better results for estimating the amount of biomass than using each sensor separately.

Remote sensing is the most important method for the estimation of biomass and is considered to be one of the most important methods for collecting data because it has the lowest direct contact with objects and phenomena. With this framework, however, although field methods are very accurate, these methods are also very time-consuming, expensive and, in some cases, cause destruction to the forest, and are practical for small and accessible areas, and the models used are error-prone. To solve the problems and to measure biomass and its production, new and controllable methods, as well as remote sensing technology, should be used.

There are no global and local equations for estimating biomass, and most available methods are ambiguous in accurate estimating. In recent studies, each of these equations has a lack of information described below:

1. Only optical images are used to estimate biomass.
2. Only radar images are used.
3. The radar and optical images have been used, but the image type has not been suitable for the purpose of the research.
4. The traditional method (sampling) is used, which is very destructive.
5. Biodiversity and species diversity are not considered
6. Biophysical and biochemical parameters are not properly selected in relation to the image and sensor.
7. There are no exact equations for biomass prediction.

Galidaki et al. (2017) emphasized the importance of biomass estimation using remote sensing and focusing on forests and other forest areas in the Mediterranean ecosystem, and on the role of forests in the carbon cycle, energy generation potential, and carbon valuation for climatic change modeling. In this study biomass is divided into two parts:

1. AGB: Above-Ground Biomass including stems, trunks, branches, shells, seeds, and leaves.
2. BGB: Below-Ground Biomass including all roots larger than 2 mm in diameter.

Most research and biomass estimates are concentrated on AGB. In the Mediterranean forests and other biotic forests, there are bushes and trees, shrubs, under-bushes, and herbaceous plants that are indicated using optical data.

Nelson et al. (2017) in the work of observations of groundwater, air, and above-ground biomass satellites in the United States and Mexico are estimated using hybrid evaluations. Biomass has been estimated using optical and SAR images by Sadeghi, (2010) and with the advice of Professor Schiama. In this thesis, limited data from ground and remote sensing techniques for Guilan forests in the north of Iran have been used. The samples were collected from the forest and parameters such as height and diameter of the tree were calculated in 28 pieces with dimensions of 900 square meters. Then, using optical and radar images, the relationship between remote sensing data and forest biomass data was estimated through regression and artificial neural network equations. According to Ramezani and Sahebi, (2015), the biomass amount can be estimated using SAR and optical images.

In general, the three steps that are expected for biomass estimation are as follows

1. Extracting the attributes of the images
2. Selecting the attributes using a genetic algorithm
3. Biomass estimation with different equations, for example, neural network or regression analysis

In a study, Amini and Sadeghi (2013) modeled the biomass of Guilan forests, in the North of Iran using optical and radar images. They considered it as the best model.

In the fifth Conference on Iranian Islamic Pattern, the development of the basic progress pattern in 2016, the Geoeye Sensor, which has a high sensitivity, has been used in forest science (Mahdavi Saeidi et al., 2020; Baharluie & Azizi, 2016). This sensor has been evaluated in estimating the number of trees per hectare (Mazandaran tourism forest) and forest trees' biomass (Ekazava reserve forest). This study shows that the use of this sensor is very accurate for forest studies and other applications. With high spatial resolution, it is possible to get a precision of 3 meters without using ground control points. The use of up-to-date data is essential for environmental planners, Earth scientists, land resource managers, and decision-makers (Karl & Maurer, 2010).

LU et al. (2004) examined biomass estimations in young and dense forests using satellite images in the Amazon basin. In this research, various plant indexes, and tissue analysis were investigated. A multivariate regression model has been created for a variety of image extraction indexes such as image bands, plant indexes, tissue properties, and plant data. This work showed that image bands and plant indexes could not be separately used as an effective model for estimating biomass. However, multivariate regression models including texture and signature spectrum, improved biomass estimates, and especially the models developed cover high-density areas. The best way to model biomass is to combine radar and optical images.

Several studies have been conducted to design methods and models for measuring forest biophysical parameters (such as canopy, leaf area index, biomass, and age of trees). However, methods based on remote sensing techniques used to examine this issue have some restrictions. Since radar images can provide accurate information from the trunk of the trees due to the use of macro-wave bands and side-looking geometry, there is a strong link between the biomass and the backscattering of radar images with combined aperture (SAR). Therefore, complementary use of this kind of data can provide a better and more comprehensive model for computing biomass.

It should be noted that one of the factors affecting the correlation coefficient of above-ground biomass model data and ground measurements is the magnitude of the error in measuring ground data. Providing a comprehensive and standardized guide is essential for ground data collection across the country and careful monitoring of how it is to be taken.

Image segmentation followed by visual interpretation of composite PALSAR images was used to delineate mangrove areas. Mangrove height and aboveground biomass were mapped using the SRTM DEM, which was calibrated with field-measured data via quantile regression models. The overall accuracy of land cover classification was 94.38% with a kappa coefficient of 0.94 when validated with field inventory data and Google Earth images (Lu et al., 2012; Aslan et al., 2016).

The model estimates of mangrove biomass were within 90% confidence intervals of area-weighted biomass derived from field measurements. When validated at the landscape scale, the difference between modeled and measured aboveground mangrove biomass was 3.48% with an MAE of 105.75 Mg/ha. are reliable for mapping and monitoring mangrove composition, height, and biomass in large areas of Indonesia.

Dube and Mutanga, (2015) in sub-Saharan Africa evaluated the utility of the Landsat 8 medium resolution (OLI) large-bandwidth multispectral dataset in quantifying AGB in forest plantations.

using two non-parametric algorithms: stochastic gradient boosting and random forest ensembles.

The results of the study show that the medium-resolution multispectral Landsat 8 OLI dataset provides better AGB estimates for Eucalyptus dunii, Eucalyptus grandis, and Pinus taeda especially when using the extracted spectral information together with the derived spectral vegetation indices.

Declarations

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