
Lei Tian 1,2,*, Xiaocan Wu 1, Yu Tao 1,3, Mingyang Li 1,*, Chunhua Qian 4, Longtao Liao 1 and Wenxue Fu 2

Abstract: Quantifying forest aboveground biomass (AGB) is essential for elucidating the global carbon cycle and the response of forest ecosystems to climate change. Over the past five decades, remote-sensing techniques have played a vital role in forest AGB estimation at different scales. Here, we present an overview of the progress in remote sensing-based forest AGB estimation. More in detail, we first describe the principles of remote sensing techniques in forest AGB estimation: that is, the construction and use of parameters associated with AGB (rather than the direct measurement of AGB values). Second, we review forest AGB remotely sensed data sources (including passive optical, microwave, and LiDAR) and methods (e.g., empirical, physical, mechanistic, and comprehensive models) alongside their limitations and advantages. Third, we discuss possible sources of uncertainty in resultant forest AGB estimates, including those associated with remote sensing imagery, sample plot survey data, stand structure, and statistical models. Finally, we offer forward-looking perspectives and insights on prospective research directions for remote sensing-based forest AGB estimation. Remote sensing is anticipated to play an increasingly important role in future forest AGB estimation and carbon cycle studies. Overall, this comprehensive review may (1) benefit the research communities focused on carbon cycle, remote sensing, and climate change elucidation, (2) provide a theoretical basis for the study of the carbon cycle and global climate change, (3) inform forest ecosystems and carbon management, and (4) aid in the elucidation of forest feedbacks to climate change.

Keywords: forest aboveground biomass; optical remote sensing; microwave remote sensing; LiDAR; uncertainty analysis; climate change

1. Introduction

The rapidly changing climate has severely impacted natural ecosystems and human societies worldwide, resulting in a series of ecological issues, including rising global sea levels [1], accelerated glacial melting at high latitudes and elevations [2–4], extremely severe weather [5,6], reduced food production [7], species extinction [8], and deleterious human health effects [9] which directly threaten the survival and security of human beings [10]. Global climate change imposes serious, long-term challenges to the sustainable development of human societies and has evolved into a political, economic, and environmental issue of global concern [11,12].
Forest ecosystems comprise the largest terrestrial carbon pool, storing approximately 76%–98% of terrestrial organic carbon (approximately 80% of above- and 40% of below-ground carbon) [13,14]. Moreover, forest ecosystems play a crucial role in the global carbon cycle by absorbing greenhouse gases (GHG) such as atmospheric CO$_2$, thereby reducing GHG concentrations and mitigating global climate change [15–18].

Forest aboveground biomass (AGB, the aboveground part of forest biomass) reflects the complicated relationship between the nutrient cycle and energy flow [19], providing the necessary nutrient sources and energy base for the functionality of the entire forest ecosystem [20]. In addition, AGB is a key indicator of forest ecosystem carbon sequestration capacity [21,22], productivity, structural function [23,24], and carbon sources and sinks [21,25,26]. Forest AGB estimates have been used as surrogates for aboveground carbon measurements [27]. Accordingly, AGB variations reflect the quality and condition of forest ecosystems [28,29], as well as the effects of ecological succession, natural disturbances, human activities, and climate change on forests [21,30,31]. Therefore, forest AGB estimations in the context of climate change could provide a theoretical basis for the study of the carbon cycle in terrestrial ecosystems and global climate change [18,22,32], which plays a crucial role in understanding and monitoring the response of forest ecosystems to GHG emissions [13,28,33]. In addition, the estimation of forest AGB has contributed to providing strategic guidelines for sustainable forest management [24,34], as well as rational utilization of forest resources and improvement of the forest ecological environment [14,28,29,35].

A rapid and accurate estimation of forest AGB remains challenging in forestry research [25,30]. In general, forest AGB estimation methods can be categorized as field measurements, remote sensing-based approaches, and ecological model simulations [25,36]. Field measurements entail the construction of allometric equations using tree height and diameter data measured via National Forest Inventory (NFI) data or auxiliary field plots [19,37–39]. To date, field measurements are considered the most accurate means of obtaining forest biomass data [19,40]; however, these measurements are also the most challenging on a regional scale because of the lengthy and arduous nature of ground-based measurements [30,41]. In addition, the actual amount of land inventoried tends to be quite small; for example, the United States Department of Agriculture (USDA) Forest Service Forest Inventory and Analysis program uses 1 plot per 2400 ha of land. Alternatively, remote sensing-based approaches combine ground measurement data with remotely sensed data to estimate parameters that highly correlate with AGB. This is achieved by obtaining spectral features and vegetation metrics from multi-source remotely sensed data, such as vegetation indices (VIs), canopy cover and height, texture, shaded fraction, leaf and basal area, and timber volume [31,42–45], whereafter an AGB estimation model is constructed for regional AGB mapping [37]. In addition to the two aforementioned methods, ecological model simulation is a promising tool for the dynamic assessment of regional AGB [46]. However, this approach is often location-specific, has poor applicability, and requires a large number of input parameters for which appropriate values may be difficult to obtain [47,48]. Therefore, remote sensing-based approaches remain the dominant data source for AGB mapping and estimation in different environments [30,36,49,50].

Optical remote sensing images with varying spatial, spectral, and temporal resolutions are freely available and are widely used to estimate AGB at different scales [49,51,52]. For example, moderate- and coarse-resolution data, such as those obtained from the moderate resolution imaging spectroradiometer (MODIS), are typically employed in large-scale AGB estimates for global, continental, or national regions [53,54]. Conversely, medium-resolution data, such as those obtained from Sentinel-2 and Landsat, are mainly used to estimate AGB at local scales [55–58]. Finer-resolution commercial satellite data, such as those obtained from IKONOS, QuickBird, and WorldView-2, have been employed for AGB estimation at the forest stand scale [59–61]. In addition, microwave radar remotely sensed data, including synthetic aperture radar (SAR), interferometric SAR (InSAR), and polarimetric InSAR (PolInSAR) data, have also been used to estimate AGB at regional scales with moderate spatial resolutions [62–66]. However, optical and radar data generally
suffer from signal saturation at high AGB, which limits their ability to estimate AGB in dense tropical and subtropical forests [40,67]. Recently, measurements collected using LiDAR, which is capable of acquiring tree height, canopy area, and stand density data, have improved AGB estimations in dense forests [68,69]. Furthermore, unmanned aerial vehicles (UAVs) have emerged as promising remote sensing tools over the last few decades, demonstrating enhanced applications in forest AGB estimation [70–73].

In an assimilate effort, this review aims to (1) introduce the principles of forest AGB estimation using remotely sensed data, (2) expound and assess several forest AGB data sources and estimation methods, (3) summarize the current sources of uncertainty in forest AGB estimation, and (4) encapsulate possible directions to improve the accuracy of AGB estimation.


As opposed to direct forest biomass estimations, remote sensing techniques generally evaluate forest AGB through the construction and use of parameters such as optical sensor-derived surface reflectance, VIs, leaf area index (LAI), coverage, and tree and canopy height, with the aim to establish relationships that serve as a proxy for the AGB [36]. The remote sensing techniques used to estimate forest AGB are illustrated in Figure 1. Over the past decades, remote sensing has played a critical role in estimating forest AGB at various spatial and temporal scales [18].

Figure 1. Illustration of forest aboveground biomass estimation using remote sensing techniques. Note: UAVs, unmanned aerial vehicles.

In addition to single-band information obtained via optical remote sensing, AGB estimations are commonly obtained using VIs based on live green vegetation absorbing solar radiation in red wavelengths to support photosynthesis, which include the normalized difference vegetation index (NDVI), difference vegetation index (DVI), and enhanced vegetation index (EVI) [18,74,75]. However, as green vegetation increases, the strong absorption of red wavelengths leads to a saturation effect, thereby decreasing the AGB estimation accuracy [36]. Nonetheless, several VIs, such as the renormalized DVI (RNDVI) and...
curacy [36]. Nonetheless, several VIs, such as the renormalized DVI (RNDVI) and modified simple ratio (MSR), have been developed to improve the accuracy of biomass estimation in dense vegetation areas [76,77]. For sparse vegetation covers, the orthogonal transform-based perpendicular VI (PVI), soil-adjusted VI (SAVI), and modified SAVI (MSAVI) are used to minimize interference from the atmosphere and soil background [78–80]. Moreover, remote sensing-derived texture information has been increasingly used in the estimation of forest AGB [81,82].

Additional parameters that are essential for AGB estimation include those describing the forest structure, such as tree height, diameter at breast height (DBH), and canopy height. Tree height not only reflects the biological characteristics and growth capacity of trees, but also indicates the stand quality [83]. Previous studies have demonstrated a constant AGB-to-tree height ratio (10.6 t/(hm²·m)) in closed-canopy forests using global sampling site survey data on forest age and average tree height [84]. In other words, the density of AGB per forest space was constant (1.0 kg/m³). This phenomenon (called constant aboveground biomass per forest space, BPS) was more pronounced between regions, demonstrating a small mean variation of 9.4–10.5 Mg/(hm²·m) and a global mean value of 9.9 Mg/(hm²·m) [84]. However, it is difficult to determine tree height at the plot scale, especially in tall and closed-canopy forests; therefore, it is often more practical to determine the tree height of only some individuals and then estimate the overall tree height by establishing a growth correlation between tree height and DBH [83]. Furthermore, the power law allometric equation of AGB and tree height constructed at the plot scale remains applicable on a large scale [85], which is a significant advantage of estimating AGB using remote sensing combined with ground measurements [25,36,50]. In recent years, microwave and LiDAR remote sensing have been widely used to estimate AGB. Tree height can be accurately and conveniently obtained from InSAR and LiDAR data, which has significant potential for advancement [86–88]. In addition, canopy height has been shown to provide accurate AGB estimations [89,90]. Notably, canopy height is not tree height; it depends not only on tree height, but also on the canopy and stand density of each tree [36].

LAI and forest coverage are also valuable indicators for estimating AGB [52,91]. LAI refers to the total area of plant leaves per unit land area as a multiple of the land area; thus, it mainly reflects leaf biomass [92]. At large scales, LAI-based estimation of AGB requires preliminary establishment of the relationship between leaf biomass and AGB, whereafter AGB is obtained via extrapolation [93]. At small scales, however, total AGB usually refers to the sum of the wood and foliage biomass [94]. Forest coverage refers to the vertical projection of the aboveground portion of trees as a percentage of the sample area and is commonly used for closed-canopy forests to express the tree layer coverage, which is the ratio of the area covered by the forest canopy to the ground surface area [83]. Generally, in uniform forests, a higher coverage represents a higher biomass [52]. Nevertheless, as forest coverage approaches saturation (reaching 1), biomass may continue to increase, which, to some extent, reduces the biomass estimation accuracy in high forest coverage areas [36].

After solar radiation-induced excitation, green leaves emit solar-induced chlorophyll fluorescence (SIF), an electromagnetic signal in the red and far-red spectral portions, from the core of their photosynthetic machinery. Therefore, SIF is mechanically connected to photosynthesis and thus provides a better representation of vegetation growth conditions compared to other biophysical parameters or VIs [95]. Previous studies have found that SIF is strongly related to the gross primary production (GPP) [96–98], and GPP can provide direct AGB estimations. Therefore, GPP can be obtained via SIF–GPP correlation analyses, whereas forest AGB can be estimated from the GPP data [18,98–100]. Currently, several global SIF products are available that permit forest biomass estimations [101], including the SIF datasets of Global Monitoring Ozone Experiment 2 (GOME-2) [102–104], Orbiting Carbon Observatory 2 (OCO-2) [105] and the Chinese Carbon Dioxide Observation Satellite (TanSat) [106]. Despite the low spatial resolution (40 km × 40 km at best) of the GOME-2 SIF dataset, it is the most widely used owing to its continuous spatial sampling, global coverage, and long time series. For example, Hu et al. [107] developed a method
to upscale SIF from instantaneous clear-sky observations to all-sky sums, adopting the absorbed photosynthetically active radiation (APAR) to correct for the effect of clouds on SIF, thereby deriving all-sky SIF (ASSIF) products from GOME-2 in 8-day and monthly intervals during 2007 and 2018 (Figure 2). Moreover, a good correspondence between the temporal trajectories of SIF and GPP [108] has been demonstrated on a global scale by Li et al. [109], who assessed OCO-2-detected SIF data and flux tower GPP data. They showed that a strong relationship between SIF and GPP exists at the ecosystem level and is nearly universal across various biomes. Nevertheless, when using SIF data to estimate GPP and AGB, the influence of environmental conditions and vegetation structure must be considered. Accordingly, SIF yields may be less sensitive than photosynthetic yields under stress conditions [110]; and the relationship between photosynthesis and top-of-canopy SIF measurements is complicated by leaf and plant structural effects [111].

Figure 2. Global upscaling of the GOME-2 solar-induced chlorophyll fluorescence (SIF) map based on averaged daily values over an 8-day period on the 265th day in 2018, (https://zenodo.org/record/4049762#.X3P9H2gzZPY, accessed on 26 July 2022.) [107].

Overall, forest AGB is estimated using remotely sensed data acquired over a broad electromagnetic wavelength range, from visible light to microwaves (Figure 3). In addition to the above ecological process parameters, environmental (e.g., precipitation, temperature, and atmospheric pressure), topographic (e.g., elevation and slope), and biotic (e.g., species diversity) factors also affect forest AGB estimates. Specifically, factors such as precipitation, temperature, elevation, and slope drive tree species distribution patterns, while soil resources and radiation intensity determine vegetation growth conditions, all of which influence forest AGB [112]. In addition, by taking succession, disturbance, and ecosystem processes into account, forest AGB estimation accuracy may be improved [36,113].
Figure 3. Electromagnetic spectrum and remote sensing of forest aboveground biomass (AGB). Note: MLA, machine learning approaches; NIR, near-infrared; SWIR, shortwave infrared; TIR, thermal infrared; VIs, vegetation indices; LAI, leaf area index; SIF, solar-induced chlorophyll fluorescence; GPP, gross primary production (adapted from Xiao et al. [18]).

3. Remote Sensing Procedures in Forest AGB Estimation

Forest AGB can be quantified using various remotely sensed data and methods [18,36,114–116]. Data sources include passive optical remotely sensed data, microwave remotely sensed data and LiDAR remotely sensed data, etc., estimation methods can be mainly classified into empirical models, physical models, mechanistic models and comprehensive models, etc.

3.1. Remotely Sensed Data Sources

3.1.1. Passive Optical Remote Sensing of AGB

Passive remote sensing is where the detection system of a remote sensing system does not itself carry a source of radiation. Specifically, it is a remote sensing system in which the instrument acquires and records electromagnetic information emitted by the target object itself or reflected from a natural source of radiation (e.g., the sun) during remote sensing. In contrast to passive remote sensing, active remote sensing refers to a remote sensing system that emits a certain form of electromagnetic wave from an artificial radiation source on a remote sensing platform to a target, whose reflected waves are then received and recorded by a sensor. Passive optical remote sensing is widely employed to estimate forest AGB because it is highly sensitive to vegetation canopy properties. Coarse-resolution data (250–8000 m, e.g., MODIS, AVHRR, and SPOT vegetation) are often used to estimate forest AGB at a regional or global scale [50,53,93,117]. Moreover, medium spatial resolution data (~30 m), mainly from the Landsat series (Thematic Mapper, TM; Enhanced Thematic Mapper plus, ETM+; and Operational Land Imager, OLI), Sentinel-2 Multispectral Imager (MSI), and Terra/Aqua ASTER data are applied to local- and regional-scale forest AGB estimates for different ecosystems [38,118–121]. High spatial resolution data (<5 m), such as IKONOS, QuickBird, and WorldView-2, are frequently used to calculate stand scale forest AGB [59–61]. However, such data are generally collected by commercial satellites, which limits their broader application in the field of forest AGB estimation.

Spectral reflectance, VIs, spatial texture, and forest canopy properties are the main variables derived via passive optical remote sensing for AGB estimation. VIs have been developed to minimize the influence of contributing factors that represent vegetation...
conditions, such as soil background, atmosphere, and sun-target-sensor geometry [122–125]. In addition to the commonly used VIs (e.g., NDVI, EVI, simple ratio (SR), and chlorophyll difference index), tasseled cap (TC) transformation, and principal component analysis (PCA) are also commonly used for AGB estimation [18]. Spatial texture information describes the spatial features of an image and can reflect the amount of forest AGB to some extent. This texture information can be extracted using a grayscale co-occurrence matrix, which generally uses a $3 \times 3$ window size [60,126]. In addition, previous studies have improved the accuracy of AGB estimates by including indicators that reflect forest canopy attributes, such as LAI, forest canopy density (FCD), and forest coverage [52,91,127].

Passive optical remote sensing provides one of the best tools for forest AGB estimation in terms of its multiple spatial resolutions, high temporal validity, global coverage, and low cost. However, the optical remote sensing signal has poor penetration, and mainly records information on the horizontal structure, thereby poorly representing the vertical one. Moreover, most vegetation attributes, especially tree height and DBH, are difficult to deduce from passive optical remotely sensed data. Nevertheless, some studies have combined field survey data with QuickBird panchromatic and multispectral data to map tree canopies, obtain canopy area–DBH relationships, and estimate the AGB of mangrove forests in southern Thailand [61]. Unfortunately, implementing this AGB estimation method in other regions is difficult. Furthermore, the passive optical remote sensing signal becomes saturated in very dense forests, resulting in the under- and overestimation of high and low biomass densities, respectively. Therefore, it remains difficult to accurately estimate forest AGB using passive optical remotely sensed data [18].

3.1.2. Microwave Remote Sensing of AGB

As opposed to passive optical remote sensing, microwave remote sensing technology is capable of day-and-night imaging, penetrating clouds and vegetation, obtaining information on the internal structure of forests, and is unaffected by meteorological conditions and sunlight levels. Therefore, it carries certain advantages in estimating forest AGB [21,128]. SAR mainly estimates forest AGB based on the backscatter coefficient. Different SAR backscatter wavelengths (or frequencies) and polarizations originate from different tree parts, resulting in varying AGB estimation abilities. Moreover, forest AGB is mainly estimated using the SAR X-(9.6 G, 3.0 cm), C-(5.6 G, 5.7 cm), S-(3.0 G, 10 cm), L-(1.27 G, 23.5 cm), and P-bands (0.435 G, 70.0 cm), and the HH, HV, VH, and VV polarization signals. The X-band interacts with the leaves and vegetation canopy and extracts information from the surface layer of the forest canopy, whereas the C-band penetrates the leaves and is dispersed by small branches and understory features. The L-band has a high penetration capability through the canopy surface layer and is dispersed by the main trunk and branches of the forest. Finally, the P-band, which has the greatest penetration capability, can penetrate the entire canopy, and the majority of the P-band backscattered signals are generated by the main trunk and its interaction with the ground. The four polarization combinations of SAR data are (1) HH polarization, where both the transmitted and backscattered signals are horizontally polarized; (2) HV polarization, where the transmitted and backscattered signals are horizontally and vertically polarized, respectively; (3) VH polarization, where the transmitted and backscattered signals are vertically and horizontally polarized, respectively; and (4) VV polarization, where both the transmitted and backscattered signals are vertically polarized [129].

Previous studies have found that co-polarization (HH and VV) data at longer wavelengths (e.g., P-band) are highly sensitive to changing surface conditions. Conversely, the backscattered signal from cross-polarization (HV and VH) mainly includes multiple scattering within the canopy and is less influenced by surface conditions [130–132]. For low biomass areas, such as grasslands, swamps, post-allotment stands, regenerated stands, and young forests, the backscattered signal at longer wavelengths is lower than that of the C-band; therefore, the C-band is preferred for biomass estimation in lower vegetation biomass areas [129]. Luckman et al. [133] estimated forest biomass in the central Amazon
basin and noted that the long-band (L-band) cross-polarized backscatter coefficient was more sensitive to forest AGB changes than that of the C-band, which is limited in distinguishing vegetation from bare soil under soil drought conditions. Following SAR-based forest biomass estimations in central Queensland, Australia, Lucas et al. [134] found that the C-, L-, and P-bands were saturated at varying degrees. Moreover, they demonstrated that the L-band HV polarization data obtained at incidence angles near or above 45° were the most suitable for AGB estimation at saturation levels of 80–85 Mg/ha. Hamdan et al. [135] estimated biomass via ALOS/PALSAR and found that the HV polarization backscatter coefficients had a stronger correlation with dense forests than those of HH polarization did, and the L-band backscatter coefficients had a good AGB estimation ability in mature tropical forests. Furthermore, using airborne SAR data, Schlund and Davidson [136] demonstrated that combined L- and P-band data had a higher biomass estimation accuracy than single-band data, owing to the high sensitivity of the L- and P-bands to low and high biomass, respectively.

The C-band is limited by its inability to effectively penetrate the canopy, and by its saturation level (approximately 60–70 Mg/ha). Nevertheless, these limitations can be overcome by using longer bands capable of higher forest canopy penetration (e.g., L-band and P-band) [137]. Studies have shown that the L-band and P-band usually saturate at 100 Mg/ha for complex heterogeneous tropical forest structures [138]; however, this saturation level increases to approximately 250 Mg/ha for stands with simple structures and few dominant species [134]. Moreover, in an L-band saturation study, Mermoz et al. [139] explored the relationship between the backscatter coefficient and tropical forest biomass. They found that biomass increased with increasing forest canopy density; however, the SAR backscatter coefficient showed a decreasing trend after initially increasing to a certain value and tended to underestimate high biomass values.

Although microwave radar penetration is capable of extracting vertical structure information of forest stands and is widely used in forest biomass estimation, many difficulties exist in SAR-based forest biomass estimation. SAR reflects the roughness of the land cover surface and, therefore, cannot distinguish between vegetation types. Moreover, the SAR signal is susceptible to interference from high wind speed, humidity, and temperature conditions, thereby complicating biomass estimation [21]. In addition, SAR signal saturation also affects the forest biomass estimation accuracy [130,140,141]. Fortunately, PolInSAR and tomographic SAR (TomoSAR) data, which includes BIOMASS (Europe, P-band, scheduled 2022) [142], NISAR (USA, L-band; India, S-band, postponed to 2022) [143], and TanDEM-L (Germany, L-band, scheduled 2022) [144] can effectively overcome the saturation issues in AGB estimation by directly measuring forest spatial structures [18]. Therefore, the use of PolInSAR and TomoSAR shows great promise in the near future.

3.1.3. LiDAR Remote Sensing of AGB

The two-dimensional (2D) nature of optical remotely sensed data limits their application in the direct quantification of vegetation parameters, such as tree height, canopy height, and wood volume. LiDAR is a relatively new and advanced technology that helps overcome this limitation owing to its ability to perform three-dimensional (3D) spatial analyses. LiDAR directly measures the height and vertical structure of forests by emitting laser pulses and measuring the signal return time [145–147]. Available terrestrial, aircraft, and spacecraft LiDAR data have been applied to forest AGB estimation and include two main types: small-footprint waveform LiDAR (discrete return LiDAR) and large-footprint waveform LiDAR (full-waveform LiDAR) [148,149]. The small-footprint waveform LiDAR generally has a diameter less than 1 m and a spot size smaller than the canopy width of the stand. Therefore, its practical application necessitates the addition of horizontal sampling points to compensate for the lack of vertical direction, thereby forming complete single-wood (an individual tree) sampling data to estimate stand parameters suitable for inversion of the forest parameter estimation at single-wood and sample plot scales [150]. Large-footprint waveform LiDAR, such as the National Aeronautics and Space Admin-
Terrestrial laser scanning (TLS) sensors provide very dense point cloud data at millimeter intervals for tree trunks, branches, and leaves. Branch and foliage volumes are then estimated based on the shape information fitted from the point cloud, thereby providing a non-destructive method to estimate forest AGB and for allometric equation development. Apart from AGB estimation at the individual tree level, forest AGB at the stand level has also been successfully estimated using TLS data.

Airborne laser scanners (ALS) can accurately measure forest canopy height and density. Additionally, by segmenting the canopy height model (CHM) or high-density point cloud data, ALS data can be used to quantify tree height, crown width, and crown volume that, in turn, can be used to estimate the biomass of individual trees. For example, Garcia et al. compared waveform- and CHM-based data obtained for different community biomass estimations and point cloud density effects, and pointed out that point cloud density had a greater effect on the CHM. When the point density exceeded 5 points/m², the CHM- and waveform-based data models performed similarly during the forest AGB estimation. Recently, an increasing amount of LiDAR data acquired from UAVs has been used to estimate forest AGB at the landscape scale. Furthermore, low point density ALS data are generally suitable for forest AGB estimation at the stand level or over large areas, and are combined with biomass data from field plots to build biomass estimation models. LiDAR-based regional-scale biomass surveys may require less field sampling than other remote sensing methods.

The main advantage of airborne LiDAR is its ability to collect data over large regions or even globally; however, its accuracy in forest parameter inversion estimation is affected by topographic factors, the influence of which numerous studies have aimed to reduce. For example, to reduce the effect of terrain slope on biomass estimation during GLAS application, Wang et al. proposed a novel slope-adaptive waveform metric that obtained a forest AGB estimation accuracy ($R^2 = 0.92$) unparalleled by that of previous methods. Regardless, LiDAR is limited by its high data acquisition costs, discontinuous data coverage, and small coverage area; therefore, research on its forest parameters remains restricted to specific areas and has not been widely applied for continuous biomass distribution estimation and mapping of larger areas. Nevertheless, an increasing availability of LiDAR data has accompanied the development of next-generation LiDAR systems, including the Advanced Terrain Laser Altimeter System (ATLAS) and Global Ecosystem Dynamics Investigation (GEDI). GEDI (launched December 5, 2018) is the first satellite-based LiDAR mission designed to study forests and, in conjunction with ATLAS on board ICESat-2, could facilitate large-scale forest AGB estimates.

Indeed, there have been studies that have used GEDI data to estimate biomass at regional and global scales.

### 3.1.4. Multi-Source Remote Sensing of AGB

Forest AGB depends on four parameters: tree height, density, DBH, and canopy width. However, measuring DBH directly using air- and spaceborne data is challenging. A single data source usually only enables the combined or individual observation of the other three parameters. Therefore, to facilitate accurate forest AGB estimations, the fusion of multi-source remotely sensed data is inevitable. To achieve this, passive, active, and combined passive and active remotely sensed data have been used. The forest detection parameters associated with these different remotely sensed data sources are shown in Figure 4.

Forest AGB estimations via multi-source passive optical remote sensing mainly focus on texture information provided by high-resolution optical remotely sensed data that is supplemented by medium- and high-resolution spectral information or vegetation indices. Nichol and Sarker extracted texture information using two high-resolution optical
datasets, AVNIR-2 and SPOT-5, to estimate forest AGB in Hong Kong, China. They observed a higher estimation accuracy based on texture information than that based on multispectral and vegetation indices, and achieved the highest estimation accuracy by combining the texture information from the two sensors. Bastin et al. [172] used Fourier-based textural ordination (FOTO) to extract Geoeye-1 and QuickBird-2 texture information to invert the forest AGB in the African Congo region. Accordingly, they found that the texture information extracted by optical remote sensing could largely minimize the effect of biomass saturation points.

Figure 4. Diagram of the detection of forest parameters from different sources of remotely sensed data.

Forest AGB estimation via multi-source active remote sensing is mainly based on field measurement or LiDAR data as a benchmark, combined with different bands of SAR/InSAR data to permit area extension. For example, Duncanson et al. [173] evaluated the biomass simulated by three NASA missions (GEDI, ICESAT-2, and NISAR) over Sonoma County, CA, USA, using high-resolution, locally calibrated, airborne LiDAR maps as reference data. By using these LiDAR reference maps, their method provided guidance for the inter-comparison and validation of spatial biomass estimates. Moreover, the method could be repeated for on-orbit estimates in any area with high-quality field plots and ALS data, providing good technical support for the synergistic inversion of LiDAR and SAR. Accordingly, Joshi et al. [174] estimated forest AGB in Denmark using airborne wall-to-wall discrete return LiDAR and field species trial plot data as a benchmark combined with L-band ALOS/PALSAR HV backscatter data.

The combination of active and passive remote sensing for the collaborative estimation of forest AGB predominantly relies on biomass data obtained from field sampling points or LiDAR as the benchmark and passive remote sensing or SAR data as the independent variables. Laurin et al. [175] combined ALSO-2-extracted SAR backscatter and texture information with Landsat 8-derived NDVI data for mixed forest AGB estimations in California (Tahoe) and the Alps (Asiago). Their model ($R^2 = 0.66$) confirmed that the combination of SAR and optical data complemented each other, thereby improving the estimation accuracy and reducing the saturation problem. Moreover, these results were similar to those of the LiDAR data model in the Alpine region, indicating that the combination of SAR and optical data could provide low-cost, wide-coverage, and highly accurate estimation results at the regional scale. Furthermore, Navarro et al. [176] used UAVs, Sentinel-1, and Sentinel-2 data to study mangrove AGB in Senegal. Accordingly, the use of UAV-obtained, highly accurate parameters of individual trees and the subsequent combination of Sentinel-1 and Sentinel-2 data provided more accurate forest AGB estimates than those obtained by single-sensor Sentinel-1 or Sentinel-2 at the sample level. These findings may facilitate the prospective advancement of biomass estimation in areas with poor accessibility.
Although remote sensing significantly reduces the time and costs of forest AGB estimation, additional field and data measurements are indispensable for both model construction and result validation of forest AGB estimations. In addition, considering the acquisition costs, area coverage (swath width), and limited availability of various sensors, the selection of a suitable sensor in accordance with the specific data availability, project budget, and technical skill requirements for data interpretation remains a practical challenge [177]. Table 1 summarizes the advantages and limitations of the main remote sensing sensors used for AGB estimations. The aforementioned issues should be considered alongside the information presented in Table 1, when applying remote sensing to forest AGB estimation studies to facilitate the selection of appropriate remote sensing technology/data according to the specifics of the study area.

Table 1. Summary of limitations and advantages of optical, microwave, and LiDAR sensors used for forest AGB estimations, as adapted from Issa et al. [177]. Notes: AGB, aboveground biomass; ETM+, Enhanced Thematic Mapper plus; InSAR, interferometric synthetic aperture radar; MODIS, moderate resolution imaging spectroradiometer; OLI, Operational Land Imager; PolInSAR, polarimetric interferometric synthetic aperture radar; SAR, synthetic aperture radar; TM, Thematic Mapper; TomoSAR, tomographic synthetic aperture radar.

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<td>No reliable indicators of biomass in closed canopy structure</td>
<td>Archived Landsat datasets (1972)</td>
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<td></td>
<td>Examples: Landsat TM/ETM+/OLI,</td>
<td>Not all texture measures can effectively extract biomass information</td>
<td>Small-to-large-scale mapping</td>
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<td></td>
<td>Sentinel-2, and Terra/Aqua ASTER</td>
<td></td>
<td>Cost-effective (Free)</td>
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<td></td>
<td>Fine Spatial Resolution</td>
<td>Large data storage and processing time</td>
<td>Estimate tree crown size</td>
<td>[59–61]</td>
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<td></td>
<td>(&lt;5 m)</td>
<td>High cost</td>
<td>Distinguish individual trees</td>
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<td></td>
<td>Examples: IKONOS, QuickBird,</td>
<td></td>
<td>Validation at localized scale</td>
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<tr>
<td></td>
<td>and WorldView-2</td>
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<tr>
<td>Microwave Sensors</td>
<td>Approaches involve the use of</td>
<td>Terrain affects the AGB estimation accuracy</td>
<td>All-day operation, penetration of clouds and vegetation, and independent</td>
<td>[21,128–135,137,138]</td>
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<tr>
<td></td>
<td>either backscatter values or</td>
<td>Signal saturation in mature forests at various wavelengths (C, L and P bands)</td>
<td>of weather conditions and sunlight levels</td>
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<td>interferometry techniques</td>
<td>Polarization (e.g., HV and VV) problems</td>
<td>Obtain information on the internal structure of the forest</td>
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<td></td>
<td>Examples: SAR, InSAR, PolInSAR,</td>
<td>Inaccurate AGB assessment at the species level</td>
<td>Measure forest vertical structure</td>
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<td></td>
<td>and TomoSAR</td>
<td>Cannot be applied on any vegetation type without considering stand</td>
<td>Generally free</td>
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<td></td>
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<td>characteristics and ground conditions</td>
<td>Can be accurate for young and sparse forests</td>
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</table>

[21,128–135,137,138]
### Table 1. Cont.

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<th>Limitations</th>
<th>Advantages</th>
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<td>LiDAR Sensors</td>
<td>High spatial resolution of 3D point cloud data (0.5 cm–5 m)</td>
<td>Repetitive at high cost and logistics deployment Requires extensive field data calibration Highly expensive Technically demanding Small coverage area and spatial discontinuity Lack of historical data hampers the achievement of multi-temporal dynamic monitoring</td>
<td>Obtain information on tree height, canopy area, stand density, and other spatial structures of the forest Penetrate cloud cover and canopy Potential for satellite-based system to estimate global forest carbon stock</td>
<td>[145–147,154–158,165,166]</td>
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</table>

#### 3.2. AGB Estimation Methods

With its rapid and continuing development, remote sensing technology has gradually replaced the traditional forest AGB estimation method. Forest AGB remote sensing estimation methods are mainly categorized into empirical, physical, mechanistic, and comprehensive models. Table 2 summarizes the advantages and limitations of these categories in terms of AGB estimation studies.

### Table 2. A summary of limitations and advantages of the main methods used for estimating forest aboveground biomass (AGB). Notes: ANN, artificial neural networks; GB, gradient boosting; KNN, k-nearest neighbor; LR, linear regression; ME, maximum entropy; MR, multiple regression; RF, random forest; SVM, support vector machine.

<table>
<thead>
<tr>
<th>Methods</th>
<th>Descriptions</th>
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<tr>
<td>Empirical modeling</td>
<td>Parametric model Includes: linear regression (LR), multiple regression (MR), and non-linear regression models</td>
<td>Requires optimized assumptions for data distribution Difficult to increase the scale and to apply to the whole area</td>
<td>Describe the model through equations and functions Simple and intuitive empirical formulas Easy to understand and interpret the results</td>
<td>[60,178–183]</td>
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<td></td>
<td>Non-parametric model Includes: k-nearest neighbor (KNN), artificial neural networks (ANN), support vector machine (SVM), random forest (RF), gradient boosting (GB), maximum entropy (ME), and deep learning (DL)</td>
<td>Requires highly accurate training data Generally slow training process Risk of over-fitting Complexity Low interpretability</td>
<td>The overall distribution of the sample does not make any assumptions Direct sample analyses High prediction accuracy Automated Transferability</td>
<td>[29,31,54,184–190]</td>
</tr>
<tr>
<td>Physical modeling</td>
<td>Includes: radiative transfer model and geometric optical model</td>
<td>Complicated calculation process Only available for small areas</td>
<td>Clear physical meaning Good model stability and applicability</td>
<td>[191–193]</td>
</tr>
<tr>
<td>Mechanistic modeling</td>
<td>Includes: climate-related models, physiological–ecological process models, and light-use efficiency models</td>
<td>Extremely complex mechanisms Requires numerous parameters and is not easily accessible</td>
<td>Clear physical meaning High prediction accuracy</td>
<td>[194–198]</td>
</tr>
<tr>
<td>Comprehensive modeling</td>
<td>Includes: FAREAST, LANDIS/LANDIS-II, FVS, and SORTIE-ND model</td>
<td>Requires numerous parameters and is not easily accessible Requires large amount of information on tree species</td>
<td>Logical mechanism, flexible structure, and variety of forms</td>
<td>[199–205]</td>
</tr>
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</table>
3.2.1. Empirical Modeling

Empirical modeling is the most common approach for estimating forest AGB. Specifically, a statistical model is constructed between variables from remotely sensed data and field samples, and the model is used to predict AGB for areas [40, 58, 119]. Empirical models are classified as being either parametric or non-parametric. Parametric models mainly refer to linear regression (LR), multiple regression (MR), and non-linear regression approaches, whereby the parametric equations and functions serve as model descriptions. Although empirical models are straightforward and understandable, which facilitates the comprehension and analysis of the findings, their estimation accuracy is typically not very high [178–181]. For instance, Safari et al. [179] used various spectral variables derived from the Landsat 8 OLI to remotely estimate the AGB using nine modeling techniques, including parametric, semi-parametric and non-parametric methods, and compared the accuracy of the different modeling techniques. Based on cross-validation statistics, SVM and Cubist regression are more accurate in the estimation of AGB and are good modeling choices if the degree of under- or over-estimation is not a problematic.

The MR model can enhance AGB estimations by integrating surface reflectance, VIs, and biophysical factors [206]. Accordingly, Eckert [60] created a biomass and carbon estimation model based on stepwise multiple linear regression using texture measurements, VIs, and forest inventory data from the WorldView-2 satellite. They demonstrated that the texture measurements had a stronger correlation with carbon and biomass than spectral characteristics. Zaki et al. [182] used a non-linear regression equation of quadratic functions to estimate the accuracy of AGB and carbon stocks in the tropical lowland dipterocarp forest of the Ayer Hitam Forest Reserve, Selangor. Their results showed a strong relationship between the projected canopy area and carbon stocks. Nevertheless, forest AGB and carbon stocks may be quantified over a wider sample area using Worldview-3 images in conjunction with CHM raster-based LiDAR. Model variable optimization is dependent on the study region, which restricts the applicability despite numerous MR models having been established for forest AGB prediction [18, 183]. Additionally, MR assumes that the data variables from remote sensors at various spectral bands are uncorrelated, which is rarely the case in remote sensing. Therefore, Lu et al. [207] suggested the use of the correlation coefficient and stepwise regression analyses to identify remotely sensed data variables that are highly correlated with biomass while being weakly autocorrelated.

Parametric models are constructed based on ideal data distribution assumptions, such that the data distribution follows a normal distribution. However, the interactions between the remote sensing component variables used to estimate forest AGB are complicated, and the data distribution is either difficult to assess or lacks distinguishing features. In contrast, non-parametric models involve direct statistical data analyses without relying on generalizations of the sample’s distribution as a whole. Non-parametric models, which are commonly applied in machine learning, are the most currently used models in remote sensing-based forest AGB estimations and mainly include k-nearest neighbor (KNN) [54], artificial neural networks (ANN) [184], support vector machine (SVM) [185], random forest (RF) [186], gradient boosting (GB) [29], and maximum entropy (ME) [187]. RF and ME methods are increasingly being applied to AGB mapping in complex environments because they can effectively integrate variables with different statistical distributions to provide stable and valid models. In addition, deep learning (DL) methods also have shown great potential in the field of forest AGB estimation [188–190, 208]. For example, DL methods not only automate many of the steps involved in AGB estimation, e.g., data processing and feature extraction, but also integrate multiple data sources such as satellite imagery, LiDAR data, and ground-based measurements to improve the accuracy of AGB estimation. Moreover, DL models have a high transferability, i.e., DL models trained on one forest can be transferred to other forests with similar characteristics, saving time and effort in model development. However, DL methods still have some limitations, such as high data requirements, complex models and low interpretability. Therefore, it is important to
carefully evaluate the advantages and disadvantages of DL methods and consider them in the context of specific applications and datasets.

The relationship between the output results and the input variables is typically complex in non-parametric models because they lack empirical formulae similar to those found in parametric models; however, it is frequently possible to achieve high model estimation accuracies. Reese et al. [209] used Landsat 5 TM and SPOT-3 imagery in combination with digital map data and forest inventory plot data to continuously estimate forest parameters (wood volume, age, and biomass) in five Swedish regions using the KNN method. Their validation results showed that the forest parameter estimation errors were lower in larger areas than in smaller areas. Gao et al. [184] used Landsat 5 TM and ALOS/PALSAR images to estimate the AGB of subtropical forests in Zhejiang Province using ANN, SVM, RF, KNN, and LR models. After comparing the estimation performance of the different models, they demonstrated that Landsat TM imagery provided more accurate AGB estimates than ALOS/PALSAR. Moreover, the combination of TM and PALSAR data performed similarly for ANN and SVM, worse for RF and KNN, and slightly better for LR.

RF improves prediction accuracy by building a “forest” of multiple categorical decision trees through an exhaustive scheme, where both samples and variables are processed simultaneously via the bootstrap method and “bagging algorithm,” respectively [29,210]. In addition, RF achieves optimal segmentation at each node using classification and regression trees. Although individual trees may be weak, the combination of all trees is more robust than the other algorithms and is not limited by the occurrence of over-learning [210]. Accordingly, Chi et al. [211] used Landsat TM, ICESat/GLAS, and ground elevation data combined with ground survey data to collaboratively estimate forest AGB in the Changbai Mountain region based on statistical regression and RF. The results showed that VI contributed more to forest AGB < 150 t/hm², whereas canopy depression contributed the most when biomass ≥150 t/hm². Furthermore, Li et al. [29] constructed and comparatively analyzed the ability of LR, RF, and extreme gradient boosting (XGBoost) models to estimate forest AGB in the Hunan Province using Landsat 8 OLI imagery and forest resource survey data. Accordingly, they highlighted the importance of variable selection to improve the performance of models, especially for machine learning algorithms, and that the influence of variable selection on XGBoost is significantly greater than that of RF. Therefore, AGB modeling based on forest type is a very advantageous for improving performance at lower and higher values of AGB.

The ME algorithm is a general statistical method used to predict values from incomplete sample datasets. It fundamentally estimates the probability distribution function of a target from a finite number of samples. The information describing the probability distribution function of the target is called “features”, with the constraint that the expected value of each feature should match its empirical mean (average value obtained from the sampling points). For forest AGB estimation using remotely sensed data, the environmental constraint information can be derived from the spectral information of remote sensing image data (e.g., MODIS, ALOS, shuttle radar topography mission, SRTM, Landsat). Furthermore, the ME model could contain many attributes and thus is highly suitable for large-scale forest AGB mapping [212]. Saatchi et al. [213] successfully developed a global, tropical forest biomass (aboveground and belowground) distribution map using an ME algorithm based on fourteen remotely sensed variables (five MODIS NDVI, three MODIS LAI, four quick scatter meter, QSCAT, and two SRTM derived metrics). Additionally, Rodriguez-Veiga et al. [214] used the ME algorithm to generate forest AGB distribution maps, corresponding biomass uncertainty distribution maps, and forest probability distribution maps for Mexico based on MODIS VI products (NDVI, EVI, blue, red, MIR, and NIR), ALOS/PALSAR mosaic data (HH, HV; two backscatter intensities), and SRTM DEM data. The analysis revealed that ALOS/PALSAR data had the highest relative contribution to AGB estimation (50.9%), followed by MODIS VI (32.9%), whereas SRTM DEM had the lowest contribution. In addition, the forest probability distribution map obtained by the ME algorithm produced the most accurate statistical results for forest AGB.
3.2.2. Physical Modeling

Biomass can be estimated by physical modeling via the inversion of remote sensing information using the relationship between bidirectional vegetation characteristics and biomass. Physical models used for forest AGB estimation primarily include the radiative transfer and geometric optical models. Koetz et al. [191] used LiDAR and optical remotely sensed data to estimate forest AGB by inverting forest structural parameters, such as vegetation cover, LAI, and tree height, using a radiative transfer model. Accordingly, a priori information on canopy structure obtained from large-footprint LiDAR data significantly improved the forest AGB estimation accuracy. Additionally, Chopping et al. [192] used multi-angle reflectance data from the NASA multi-angle imaging spectroradiometer on the Terra satellite as a geometric optical model to invert the canopy cover and mean canopy height and derive the forest AGB by linear transformation in the forests of Arizona and New Mexico, USA. The retrieved distributions of forest crown cover, mean canopy height, and AGB were similar to maps obtained from the USDA Forest Service. Although the physical model has a clear physical meaning and a good stability and applicability, the calculation is complicated and is currently only applicable to small-scale AGB estimations [193].

3.2.3. Mechanistic Modeling

Mechanistic (or process) modeling is generally used to simulate the net primary productivity (NPP) of a forest, and is based on the principles of plant physiology and ecology. Models in this category estimate the productivity of vegetation by simulating the conversion of solar energy to chemical energy during vegetation growth, photosynthesis and evapotranspiration in the plant canopy, and the accompanying water loss from the plant body and soil [194]. Common mechanistic models include climate-related, physiological–ecological process, and light use efficiency models [193,195]. Climate-related models estimate the NPP of different zones based on the average annual temperature, precipitation, and soil moisture [196]. Furthermore, the physiological–ecological process model uses information, such as vegetation cover and soil moisture, provided by remotely sensed data to simulate ecological and physiological factors related to the environment and to plant growth, respectively, to form a hybrid biochemical and biophysical model [197]. Light use efficiency models estimate vegetation NPP by utilizing the relationship between vegetation NPP and photosynthetically active radiation absorbed by vegetation, which is converted to organic matter [197,198].

Opposed to empirical models, mechanistic models emphasize the simulation and description of various processes acting within the ecosystem; therefore, the estimation results are more reliable. However, mechanistic approaches are highly complex and require the input of numerous parameters, such as plant physiology and ecology, soil, meteorology, and solar radiation, some of which are not readily available, thereby limiting their applicability [194].

3.2.4. Comprehensive Modeling

Comprehensive models use ecologically significant estimation models combined with remotely sensed data to estimate forest AGB. These models employ ecological succession as the theoretical basis and allow dynamic simulation of forest vegetation changes [204], including the widely used FAREAST, LANDIS/LANDIS-II, FVS, and SORTIE-ND models [199–203]. For instance, based on the FAREAST model, Wang et al. [205] used the distribution range of *Picea crassifolia* on different elevation gradients to simulate the elevation distribution characteristics of biomass carbon in young and middle-aged forests in the western, central, and eastern Qilian Mountains. Their results showed that the biomass carbon of *P. crassifolia*, which was distributed between 2800 and 3100 m above sea level, was higher in the central part of the Qilian Mountains than in the eastern and western parts, thereby identifying the best area for *P. crassifolia* growth and potential distribution. Wu et al. [199] used a loose-coupling of PnET-II with LANDIS-II to simulate changes in forest AGB and composition under climate change scenarios (current climate, RCP2.6, RCP4.5,
RCP6.0, and RCP8.5) with harvest disturbances. The simulation results demonstrated that forest AGB and composition were significantly affected by climate change in both landscapes. Changes in forest AGB was mostly driven by succession and harvest, but climate change also greatly contribute to the variation in AGB of deciduous broad-leaved forests, and coniferous forests. Overall, comprehensive models are logical, flexible in structure, and diverse in form; however, when the spatial resolution of the remotely sensed data is low, the extracted remote sensing information, such as light, moisture, soil nutrients, and temperature, cannot reflect the forest ecological succession law. Comprehensive models require the input of parameters of many tree species. Therefore, the model accuracy not only depends on that of the remotely sensed data, but also on the accuracy of these parameters. This makes the estimation of forest AGB challenging in areas without comprehensive information on the biological characteristics of tree species [193].

4. Uncertainty in Remote Sensing Estimation of Forest AGB

To date, a large, global body of research exists wherein increasingly reliable forest AGB estimations have been achieved using various remotely sensed data and techniques [43,48,91,137,180]. However, the accuracy of remote sensing-based AGB estimations has been a cause of great concern because accurate forest AGB estimation is required to effectively study the global carbon cycle and climate change [18,25]. The forest AGB calculation accuracy is affected by a variety of possible errors and uncertainties, which lead to underestimation of high and overestimation of low AGB values [215,216]. In general, the causative factors of the errors and uncertainties in remote sensing-based forest AGB estimations include remote sensing images, sample plot survey data, stand structure, and statistical models [217,218].

Remotely sensed data errors are primarily related to image complications (e.g., image surface reflectance, VI, SIF, and LAI products) brought on by environmental factors (e.g., atmosphere and humidity), sensor degradation, faulty image processing techniques, and faulty matching of image acquisition time with sample sites, among others [219,220]. Errors in sample plot survey data include faulty measurements of single trees (e.g., DBH and height), allometric growth equation calculations of the sample plot biomass, and sample plot location matching to remote sensing image data [218]. In addition, different sources of forest inventory data may also cause uncertainties in the AGB estimates [218]. For example, in the United States, the USDA Forest Service, Forest Inventory and Analysis program provides NFI data collected as a probability-based (semi-systematic) sample to be used for the purpose of, among others, calibration of forest biomass estimation and mapping. Similarly, ecological research networks such as the National Ecological Observatory Network (NEON), Forest Global Ecosystem Observatory (ForestGEO), and others provide fewer sampling locations but a wealth of data (including commissioning their own remote sensing). Different sources of field survey data use inconsistent measurement methods or approaches, which is one of the sources of the uncertainties in the final AGB estimates. Stand structure errors primarily refer to the inability of information, such as stand canopy, stand age, tree height, and tree diameter structure, to fully portray the stand state on remote sensing imagery. Finally, statistical model errors are mostly caused by the model’s failure to accurately link the stand information with remote sensing image components, leading to estimation issues. Examples of such errors include errors in input data other than remotely sensed data (e.g., meteorological data), errors in the model structure (e.g., incomplete or flawed underlying processes and assumptions), and errors in model parameters (e.g., incomplete or poorly defined parameters due to a lack of information) [18].

Numerous studies have evaluated the uncertainty of remote sensing forest AGB estimations [214–216,221]. Accordingly, Saatchi, Houghton, Alvala, Soares and Yu [41] used a regression model to examine the spatial distribution of forest biomass in the Amazon basin and found a significant correlation between forest AGB distribution and the length of the dry season, as well as a 20% uncertainty in the estimated total carbon. Using Landsat TM images and permanent sample plot data from the national forest inventory,
Zhang et al. [222] investigated the calculation uncertainty of the aboveground forest carbon (AGFC) owing to sample plot location errors. The findings demonstrated that the accuracy of the anticipated AGFC values decreased with increasing perturbation of the plot location distance. In addition, it was discovered that upscaled spatial data reduced the effects of plot location errors on the map accuracy compared to those without upscaled spatial data. Fassnacht et al. [223] examined the effects of sample size, statistical models, and different remotely sensed data on forest AGB estimation. They found that the sensor type was the most significant factor affecting the accuracy of AGB estimation (LiDAR outperformed hyperspectral results), and that using hyperspectral data in conjunction with LiDAR did not improve the prediction accuracy, and that the prediction models, which usually had a greater impact than the sample size, had a significant impact on the accuracy of the estimation result. Fu et al. [224] examined the biomass estimation uncertainty caused by sampling and model estimation errors in the anisotropic growth equation from continuous forest inventory data of the Chinese fir in Jiangxi Province. Accordingly, they found that the sampling error had a greater effect than the model estimation error on biomass estimations. Furthermore, Gao et al. [184] explored the effects of different models on forest AGB estimation and found that high value underestimation and low value overestimation occurs with different models and images from different data sources (Landsat and SAR). The effect of models on AGB estimation is significant, however, the ability of different models to portray different AGB intervals varies. Therefore, model selection is an important consideration to ensure accurate AGB estimation. In addition, the forest AGB estimates for some specific areas are also of interest, such as the wildland–urban interface (WUI) [225]. WUI, where built-up intermingles with wildland vegetation, is the fastest-growing land use type in the United States [226]. Some studies have shown that forest in the WUI had greater carbon storage, with greater aboveground biomass, relative stand density, and more live trees per hectare than non-WUI forest, suggesting a greater capacity to sequester carbon compared to non-WUI forest [226].

Forest stand structures include both horizontal and vertical structures, and the structure of forest ecosystems is relatively complex. Remote sensing-based forest biomass estimations are carried out using stand structure information, which is, therefore, an important factor affecting forest biomass estimation errors and inaccuracies. To establish empirical correlations between continuous estimates of forest structural features and remotely sensed image data (described as spectral response variables), Hall et al. [56] proposed BioSTRUCT (Estimating Biomass from Stand STRUCTure) to estimate forest AGB. Their results suggested that stand structure may significantly improve the accuracy of AGB estimation. Additionally, Zheng et al. [227] developed a polynomial model to improve the accuracy of forest AGB estimations by combining the spectral variables of Landsat images with the age of the forest stands. Similarly, Ou, Li, Lv, Wei, Xiong, Xu and Wang [186] improved alpine pine forest AGB estimation accuracies by adding age group independent variables to the model. Specifically, different vegetation types are represented in remote sensing images as having different spectral information, and in this case, the forest needs to be classified into types to improve the accuracy of remote sensing-based forest AGB estimations [228]. Nevertheless, forest stands contain not only tree layers, but also shrub and herb layers. In underdeveloped stands, the remote sensing images also contain shrub and herb information to a certain extent, which affects the forest AGB estimation accuracy.

Forest AGB mapping based on different remote sensing data and methods may vary significantly. Several forest AGB maps, some of which are based on ground-measured forest data, optical remote sensing data, or products, have been developed for China (Figure 5). For instance, Piao et al. [229] developed a satellite-based method to estimate the total forest biomass carbon stocks in China based on forest inventory data from three periods (1984–1988, 1989–1993, and 1994–1998) and synchronous NDVI data, thereby successfully estimating these forest AGB changes over two decades (1981–1999). Du et al. [230] estimated the spatially explicit distribution of forest AGB in China based on forest inventory statistics (2004–2008) and the spatially explicit MODIS land cover type product (MCD12C1).
Moreover, Yin et al. [231] integrated the plot-level ground-measured forest AGB database with geospatial information from a MODIS dataset (1 km spatial resolution) into a model tree ensemble algorithm to estimate forest AGB in China during 2001–2013. Interestingly, some maps combine ground-based measurements, optical remote sensing, spaceborne LiDAR, and SAR data to estimate forest AGB. Su et al. [232] developed a 1000 m resolution forest AGB map of China using forest ground survey data, GLAS/ICESat data, optical imagery, climate surfaces, and topographic data. Furthermore, Huang et al. [25] developed a finer-resolution spatially continuous forest AGB map for China. They developed novel forest type- and ecozone-specific allometric models based on 1607 field plots, and subsequently applied these models to GLAS data to calculate AGB at the footprint level. This GLAS footprint AGB was related to various variables extracted from Landsat and PALSAR L-band data to map the 30 m resolution national forest AGB. Nevertheless, other studies have conducted global forest AGB mapping based on previously published land-cover biomass products. Spawn et al. [233] developed a global 300 m spatial-resolution, vegetation biomass, carbon-density product based on GlobBiomass AGB density maps [234], and African vegetation AGB density maps [44]. Numerous studies have obtained significantly different average forest AGB values (69.88–120 Mg/ha) for China (Figure 5 and Table 3). Notably, we used an AGB-to-carbon conversion factor of 0.5, and the forest biomass (above- and belowground)-to-AGB conversion factor of 0.81, thereby converting forest biomass and carbon-to-forest AGB [235]. The highest average AGB was observed for the product of Su et al. [232], and that of Yin et al. [231] was similar. It is essential to quantify and reduce uncertainty in the remote sensing of forest AGB products to assess regional and global carbon storage to inform the management and climate policy making.

Figure 5. Forest aboveground biomass (AGB) maps of China based on different datasets: (a) the Huang et al. map [25]; (b) the Su et al. map [232]; (c) the Spawn et al. map [233]; (d) the average AGB of six China forest AGB products.
Quantifying and reducing the uncertainty in forest AGB estimates remains a significant challenge. Considering the different sources of uncertainty, it is important to comprehensively quantify the uncertainty of these estimates in order to reduce or eliminate its effect on forest AGB estimation accuracy. This provides an important direction for future research on forest AGB estimation. Furthermore, the accuracy of forest AGB estimates could be improved by using high-quality resolution, and better methodological remotely sensed data while considering succession, disturbance, and ecosystem processes.

5. Prospects for Remote Sensing of Forest AGB Estimation

The urgent need for society to elucidate Earth’s carbon cycle has motivated recent studies to focus on the numerous factors that change the observed atmospheric CO$_2$ composition; however, numerous gaps remain in our knowledge of these processes. Furthermore, terrestrial vegetation contains carbon stocks comparable to the total amount of atmospheric CO$_2$, and plays an important role in the Earth’s carbon cycle.

Earth observation satellites and other remote sensing sources are the only means to obtain high spatial and temporal resolution data on a global scale. Passive optical, microwave, and LiDAR remote sensing will remain in use for AGB estimations. The utilization of remote sensing combined with field observation data allows for the assessment of global forest AGB changes. Passive optical remote sensing, with its high spatial and temporal resolution, and continuous spatial and temporal coverage, remains an important data source for AGB estimation. For example, the Harmonized Landsat and Sentinel-2 (HLS) data generated by combining Landsat 8 and Sentinel-2 data can provide data with a time interval of up to 5 days and a spatial resolution of 30 m. This enhances our capacity to estimate the AGB consistently from the local to the global scales by enabling us to estimate the AGB at a field scale of 30 m using an ideal time series [236]. Nevertheless, the large amounts of accurately measured AGB data required for empirical models based on passive optical remotely sensed data, as well as for AGB estimation models built using machine learning algorithms, remain lacking at the regional and global scales. Fortunately, high-resolution passive remotely sensed data (e.g., QuickBird, IKONOS, and UAVs) and LiDAR data can generate a large number of AGB samples to train AGB estimation models. Furthermore, the fusion of multi-source remotely sensed data (i.e., passive optical remote sensing with LiDAR and microwave remotely sensed data) is expected to partially overcome the saturation problem in passive optimal remote sensing biomass estimation [18].

To assess forest AGB and monitor forest change, data from airborne- and satellite-based SAR have become crucial resources during the past three decades. Three limitations of SAR forest AGB estimation now exist at the regional scale: the saturation problem, topographic effects, and the mismatch between the base unit of the SAR data and the field sample plot area. The saturation problem associated with AGB estimation using the radar backscatter intensity of a forest with a complex spatial structure may be significantly improved by exploiting spatial structure information obtained from other data, such as InSAR data or optical stereo images [237]. Digital surface model (DSM) data obtained using TanDEM-X satellite X-band radar interferometric data with nearly no temporal decoherence provides, when combined with a high-precision digital terrain model (DTM), a CHM that improves forest AGB estimation accuracy [238]. In addition, NASA’s NISAR provides global L-band InSAR data, as well as either PolInSAR or TomoSAR data, which will soon
be widely available free of charge. In particular, the L- and P-band data can directly invert the 3D structure of the forest canopy without requiring a DTM, providing a promising solution for mapping global biomass and monitoring forest disturbances. In practice, the terrain effects can be corrected by developing a relationship between the radar backscatter coefficient and the incidence angle of the main surface types. This involves calculating the incidence angle of each image element based on the radar incidence angle, the slope angle, and slope direction information of the local terrain. Moreover, the terrain effects will likely be overcome by the development of theoretical models and simulations \[239\], whereas the scale-mismatch problem may be overcome by the synergy of SAR with other types of data such as LiDAR \[240\] and stereo images \[241\].

In the last decade and beyond, LiDAR-based technology advancements have enabled the acquisition of accurate understory topography data and forest structure parameters. Furthermore, TLS integration with mobile systems have resulted in the development of mobile laser scanning (MLS) and backpack laser scanning (BLS). The increasing integration of ALS with hyperspectral sensors and the decreasing cost of data capture enables the use of ALS for large-scale sampling \[242\] and forest AGB estimation \[164\]. Moreover, because more satellite-based LiDAR systems are used to facilitate global carbon cycle research, AGB estimation models based on LiDAR data will require more consideration to allow regional and global biomass mapping. For example, the new LiDAR aboard ICESat-2 will provide global coverage data to assess carbon stocks, whereas GEDI will use a geodetic-grade LiDAR laser system with 25 m coverage to provide high-resolution laser-ranging observations of the 3D structure of the Earth’s surface.

The integration of passive optical remotely sensed data, SAR, and spaceborne LiDAR is expected to provide seamless and accurate AGB estimates on a global scale. Specifically, at local and regional scales, airborne acquisition techniques, such as imaging spectrometry, LiDAR, SAR, and optical photogrammetry, provide high spatial resolution data. Conversely, spaceborne sensors, including those on Landsat, MODIS, SRTM, ALOS/PALSAR, ICESAT/GLAS, and the L-band SAR carried by ALOS-2, provide observations at intercontinental and global scales.

Clearly, many forest AGB estimation methods exist based on remotely sensed data. The selection of an appropriate method depends on the coverage of the specific project and the availability of various data types. Although the established algorithms have achieved some results, improving the prediction accuracy and reducing uncertainty in the face of complex conditions is still a key direction for future research. Additionally, the use of MR models to estimate local and regional biomass is still relatively popular; however, non-parametric or machine learning approaches have a greater advantage for regional- and global-scale projects. In addition, canopy structure, tree species, and other environmental factors are important considerations for the development of biomass estimation algorithms and models, and the interference of these factors should be reduced to improve the biomass estimation accuracy.

6. Conclusions

In the context of global climate change, forest AGB estimation provides a theoretical basis to study the carbon cycle; however, rapid, accurate AGB estimation remains challenging in forestry research. Remote sensing is an advanced biomass estimation method that enables the estimation of forest AGB at different scales. At present, remotely sensed data from various platforms/sensors are widely applied to estimate forest AGB, including passive optical, microwave, and LiDAR remote sensing, which has resulted in various AGB estimation methods being proposed, including empirical, physical, mechanistic, and comprehensive models. Forest AGB-related parameters, such as surface reflectance, VIs, LAI, coverage, tree height, and canopy height, are used to develop forest AGB estimation models. However, the limitations of different remotely sensed data sources and forest AGB estimation methods remain a major challenge in carbon cycle research. Therefore, reliable forest AGB estimation necessitates the reduction or elimination of uncertainty sources.
Combining remotely sensed data from multiple sources is the most promising strategy for AGB estimation. In such a strategy, VIs, spectral, and texture information are extracted from passive optical remotely sensed data and combined with SAR/LiDAR-extracted tree height, DHB, and canopy height data to estimate forest AGB, which is expected to partially overcome the saturation problem. Forest AGB estimation methods should be selected according to the specific conditions of the study area. To date, MR models remain a relatively popular approach to estimate local and regional biomass; however, non-parametric or machine learning approaches provide added advantages for regional- and global-scale projects. Here, the key finding of this paper is that canopy structure, tree species, and other environmental factors should be considered when developing biomass estimation algorithms or models. On this basis, the interference of these factors should be reduced to improve the accuracy of biomass estimations. Overall, passive optical remotely sensed data, SAR, and airborne LiDAR remain useful for AGB estimation, while the integration of multi-source data is expected to provide seamless and highly accurate AGB estimates on a global scale.

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Abbreviations

AGB, aboveground biomass; AGFC, aboveground forest carbon; ALS, airborne laser scanners; ANN, artificial neural networks; APAR, absorbed photosynthetically active radiation; ASSIF, all-sky solar-induced chlorophyll fluorescence; ATLAS, Advanced Terrain Laser Altimeter System; BLS, backpack laser scanning; BPS, aboveground biomass per forest space; CHM, canopy height model; DBH, diameter at breast height; DL, deep learning; DSM, digital surface model; DTM, digital terrain model; DVI, difference vegetation index; ETM+, Enhanced Thematic Mapper plus; EVI, enhanced vegetation index; FCD, forest canopy density; ForestGEO, Forest Global Ecosystem Observatory; FOTO, Fourier-based textural ordination; GB, gradient boosting; GEDI, Global Ecosystem Dynamics Investigation; GHG, greenhouse gasses; GLAS, Geoscience Laser Altimeter System; GOME-2, Global Monitoring Ozone Experiment 2; GPP, gross primary production; HLS, harmonized Landsat and Sentinel-2; InSAR, interferometric synthetic aperture radar; KNN, k-nearest neighbor; LAI, leaf area index; LR, linear regression; ME, maximum entropy; MLS, mobile laser scanning; MODIS, moderate resolution imaging spectroradiometer; MR, multiple regression; MSAVI, modified soil-adjusted vegetation index; MSI, Multispectral Imager; MSR, modified simple ratio; NASA, National Aeronautics and Space Administration; NDVI, normalized difference vegetation index; NEON, National Ecological Observatory Network; NFI, National Forest Inventory; NISAR, NASA-ISRO SAR Mission; NPP, net primary productivity; OCO-2, Orbiting Carbon Observatory-2; OLI, Operational Land Imager; PCA, principal component analysis; PolInSAR, polarimetric interferometric synthetic aperture radar; PVI, perpendicular vegetation index; QSCAT, quick scatter meter; RF, random forest; RNDVI, renormalized difference vegetation index; SAR, synthetic aperture radar; SAVI, soil-adjusted vegetation index; SIF, solar-induced chlorophyll fluorescence; SR, simple ratio; SRTM, shuttle radar topography mission, SVM, support vector machine; TanSat, Chinese...
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