remote sensing

Review

Assessment of Carbon Sink and Carbon Flux in Forest Ecosystems: Instrumentation and the Influence of Seasonal Changes

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Abstract: Accurate measurement and estimation of forest carbon sinks and fluxes are essential for developing effective national and global climate strategies aimed at reducing atmospheric carbon concentrations and mitigating climate change. Various errors arise during forest monitoring, especially measurement instability due to seasonal variations, which require to be adequately addressed in forest ecosystem research and applications. Seasonal fluctuations in temperature, precipitation, aerosols, and solar radiation can significantly impact the physical observations of mapping equipment or platforms, thereby reducing the data's accuracy. Here, we review the technologies and equipment used for monitoring forest carbon sinks and carbon fluxes across different remote sensing platforms, including ground-based, airborne, and spaceborne remote sensing. We further investigate the uncertainties introduced by seasonal variations to the observing equipment, compare the strengths and weaknesses of various monitoring technologies, and propose the corresponding solutions and recommendations. We aim to gain a comprehensive understanding of the impact of seasonal variations on the accuracy of forest map data, thereby improving the accuracy of forest carbon sinks and fluxes.

Keywords: seasonal variations; forest; carbon sink; carbon flux; remote sensing platforms

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1. Introduction

To better understand the implications of current and future climate change, the direct effects of human intervention on ecosystems, and the ability to make accurate predictions, it is imperative to continuously monitor forest carbon storage and flux. This is a crucial issue for land-based climate change mitigation initiatives [1]. The science of forest management heavily relies on data collection, which is the foundation for monitoring forest carbon sinks and fluxes. Advances in observation technology have increased the precision of data collection. Different equipment is needed to observe forest structural features at different scales, and mapping instruments have long been used to track forest carbon fluxes and sinks [2].

Early forestry surveys used calipers, Vernier calipers, Wye-level prisms, and other diameter-at-breast-height measurement devices to measure individual trees [3]. Significant data mistakes arose from this approach's subjective and arbitrary nature. As surveying and mapping technology advanced, protractors replaced visual observation methods. Researchers began to use sample perimeter measurement instruments such as the compass, total station, and theodolite to set up standard plots utilizing the square grid method and measure the circumference of each tree to calculate the amount of forest stock. However, the types of forest parameters measured by this method were limited. With the advancement of forestry surveying instruments, high-precision electro-optical instruments such as electronic theodolites, dendrometers, increment borers, and total stations have become commonplace [4] (Figure 1). Around the world, a range of high-precision, real-time, recordable tree-measuring devices are now being developed. These devices not only significantly increase labor efficiency but also reduce data inaccuracy [5].

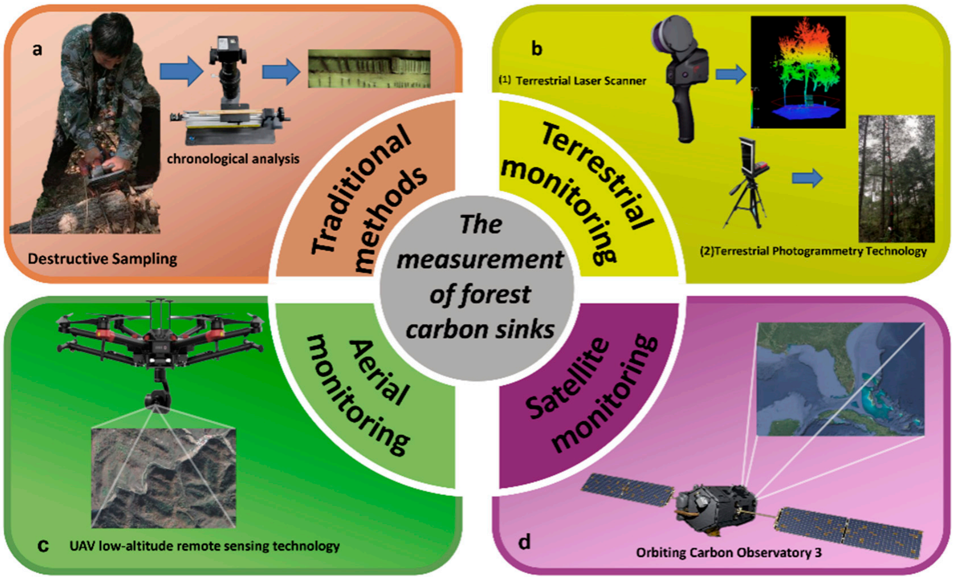

Figure 1. Diagram of monitoring instruments for forest carbon sources. Traditional methods include annual observations after harvesting of trees (**a**). Terrestrial laser scanning methods and terrestrial photogrammetry (**b**). Unmanned aerial remote sensing measurements at low and medium altitudes (**c**). High-altitude remote sensing (**d**).

Today, standard methods for data analysis and forest monitoring include remote sensing [6], high-precision electro-optical sensors, Geographic Information Systems (GIS), Global Positioning Systems (GPS), the Internet of Things (IoT) [7], and modeling [8]. The first step is to select remote sensing platforms and sensors based on the monitoring area to monitor forest parameters using remote sensing technology. Ground-based platforms are suitable for monitoring forest samples and can be equipped with sensors such as spectrometers, cameras, and radars, which are characterized by close-range remote sensing, determining the spectral characteristics and images of various features. Data collected by ground-based platforms can be used to calibrate and support aeronautical and aerospace remote sensing [9].

Aerial remote sensing is chosen for observations at the regional scale. The aerial platform is suspended in the atmosphere (troposphere and stratosphere) at an altitude of less than 80 km, characterized by low-flight altitude, better ground resolution, mobility and flexibility, fewer constraints imposed by ground conditions, shorter cycle time, and convenient data recovery [10]. Aerial remote sensing platforms include manned aircraft, drones, and balloons carrying a wide range of sensors, including cameras, video cameras, Light Detection and Ranging (LiDAR), hyperspectral imagers, microwave radar, and other sensors [11]. The spaceborne remote sensing platform allows for macro, integrated, dynamic, and rapid observations of the Earth.

It is worth mentioning that LiDAR has a wide range of applications in forestry and ecology. It can be used for digital elevation model generation, forest structure parameter extraction, forest ecosystem parameter inversion, and microhabitat diversity monitoring [12]. LiDAR can be mounted on various platforms in the sky and on the ground. Ground-based LiDAR can acquire leaf and single-tree scale information, including location, diameter at breast height (DBH), tree height, number of plants, and understory vegetation information [13]. Scholars used high-end products (TLS and UAV LiDAR) in managed forests of Central Europe to assess how fusion can increase tree structure. They found that the fusion of LiDAR technology based on TLS and UAV-LS can significantly reshape the modeled tree structures in all cases (broadleaves and conifers). This led to improved estimates of all tree metrics (crown and stem), opening the way for several precision forestry applications [14]. Satellite-mounted LiDAR is applicable at global, regional, and spot scales to obtain mean height, biomass, and carbon stocks for forest parameters [15]. These advantages are fully reflected in forestry surveys. LiDAR mainly utilizes near-infrared and visible light bands, with a wavelength ranging from 250 nm to 11 μm [16]. Its slight laser beam emission angle allows it to emit a very narrow beam with concentrated energy and good coherence, resulting in high resolution. Even smaller-scale targets can produce detectable echo signals, which provides a unique advantage for detecting small targets. In addition, LiDAR has excellent immunity to electromagnetic interference [17].

Due to various factors interfering with the actual observation process, the certainty of forest parameters is often weakened. This results in a certain degree of inaccuracy and error in the final observation results, which significantly impacts scientific research and decision-making [18]. Instrumental and technological factors are among the major causes of uncertainty. Common remote sensing techniques, such as active and passive remote sensing, can produce errors in the accuracy of the equipment used, the algorithms used to receive and process the signals, and other aspects. For example, limitations in spatial and temporal resolution can result in the loss of some detailed information [19]. In addition, the same geographic target may have different inversion results in different sensor observations due to sensor performance characteristics, operating modes, etc. [20]. The characteristics of the ground may also introduce uncertainty. Factors such as forest type, species, age, stand density, etc., can affect the results of remote sensing observations [21]. Natural environmental factors are also important factors affecting the accuracy of remote sensing observations. For example, seasonal changes, meteorological conditions, and the atmosphere's state all impact the signals received by the sensors, which, in turn, affects the accuracy of data processing and parameter estimation [22]. There is a lack of research on the effects of seasonal changes on physical observation processes using instruments.

In this regard, our work provides an overview of the equipment that has been widely employed over the past five years to measure carbon sinks and fluxes in forest ecosystems across the globe (Tables 1 and 2). We summarize the various detection instruments currently in use worldwide from three perspectives and discuss the effects of seasonality on the physical observation process. An instrumental approach to measuring carbon sinks and fluxes is presented. To contribute to global forest observations, we provide readers with a concise handbook for operating the instruments, focusing on how the usage of each device varies at different scales. The content of this study covers four main parts. First, this article reviews the primary methods for measuring carbon sinks and fluxes in forest ecosystems, subdivided into non-real-time monitoring and real-time monitoring. Next, this article elaborates on using ground-based LiDAR to provide readers with clear guidelines and references in practical operations. In the third part, we focus on the application of airborne LiDAR and give a detailed analysis of its advantages and challenges in measuring carbon sinks and fluxes. Finally, this article discusses the importance of spaceborne remote sensing in global forest observation.

Table 1. Comparison of forest carbon sink research methods.

Categorization	Methods	Instrumentation	Scale	Advantages	Limitations
Direct measurement	Traditional measurement methods	Diameter tape; calipers; Blume–Leiss; ultrasonic altimeter; Abney level; clinometer; Santos inclinometer; DQL-9 altimeter compass.	sample plot	Low cost of equipment	Equipment does not store data in real time and relies on manual operation.
	New sample survey methodology	Electronic protractor; handheld total station.	sample plot	The device can acquire multiple parameters and record the data in real time.	Instruments are not widely available.

Table 1. *Cont.*

Categorization	Methods	Instrumentation	Scale	Advantages	Limitations
Remote sensing measurements	Optical measurement methods	Theodolite; total station.	sample plot	High-precision equipment, simple operation, real-time data recording.	Limited measurement range, expensive equipment, and limited penetration capability.
	LiDAR	Airborne LIDAR; backpack LIDAR; ground-based LIDAR.	local/strip /sample plot	High precision, high efficiency, strong penetration.	High cost, sensitivity to environmental conditions, limited penetration capability, complex data processing, high energy consumption, line-of-sight limitations.
	Photogrammetric methods	Aerial cameras; panoramic cameras; infrared sensors.	local/strip /sample plot	Flexibility, controllability, low cost.	The effect of light and weather, large amount of data, cumbersome post-processing, and limited accuracy.
	Remote sensing of forestry	Optical remote sensing; SAR.	global/regional/ local	High spatial resolution, multi-spectral information, non-contact measurements (Optical remote Sensing). Penetration capability, all-weather, all the time (SAR).	Optical remote sensing is susceptible to weather, light-dependent, and has limited penetration capabilities. High equipment costs, large data volumes, sensitivity to electromagnetic interference, limited depth penetration, noise issues (SAR).

Table 2. Comparison of forest carbon flux research methods.

Methods	Principle	Instrumentation	Application Range
Eddy covariance	Measurement of gas concentrations and flow velocities above forests using 3D anemometers and infrared gas analyzers, with net ecosystem carbon exchange (NEE) obtained by calculating covariates.	3D Sonic anemometer (CAST3, Campbell Scientific, Inc. Logan, UT, USA), CO_2/H_2O infra-red gas analyzer; data collector (CR1000, Campbell Scientific, Inc. Logan, UT, USA); atmospheric temperature and humidity sensors (HMP45C, Vaisala, Helsinki, Finland); open-path or closed-path infrared gas analyzer (Li-7500, Li-Cor Inc., Lincoln, Nebraska, USA); net radiation sensor (CNR4, Kipp&Zonen, Delft, Holland); soil temperature sensors (109, Campbell Scientific, Inc., Logan, Utah, USA); soil moisture content sensors (CS616, Campbell Scientific, Inc., Logan, Utah, USA).	Regional and global
The box method	Physiological; mathematical calculations.	Infra-red gas analyzer; gas chromatograph.	Low-vegetation ecosystems such as farmland and grasslands
Remote sensing	Sensors; electromagnetic radiation; digital imaging; laser.	Terra; aqua; landsat.	Large area

Table 2. *Cont.*

Methods	Principle	Instrumentation	Application Range
Biomass method	Use the sample plot data to obtain the average biomass per unit area of vegetation and multiply the average biomass by the area of the forest type.	Electronic balances; weighing stations; biomass sample collection tools.	Wide range of applications
Modeling approach	Indirect calculation of systemic carbon fluxes based on long-term observations in multiple sites or studies of carbon stocks in small individuals and scale transformations.	--	Wide range of applications
Chemical method	Alkali absorption	Gas chromatograph (GC); infra-red gas analyzer (IRGA).	Wide range of applications

-- indicates no data.

2. Basic Measurements of Forest Carbon Sinks and Fluxes

Monitoring methods for forest ecosystems can be categorized into two main types: non-real-time tracking; and real-time monitoring. Non-real-time tracking refers to monitoring over years or decades, while real-time monitoring refers to monitoring over weeks. Inventory and system modeling inference methods are non-real-time tracking methods, while remote sensing and atmospheric inversion are real-time monitoring methods. Inventory method: This method involves obtaining standard wood biomass through destructive sampling and modeling the anisotropic growth of biomass using easily measurable variables such as diameter at breast height (DBH) and tree height. This method is widely used in carbon cycling studies within forest ecosystems. However, it is labor-intensive and challenging to implement on a large scale [23,24]. System Modeling Inference utilizes methodological modeling strategies and standard nonparametric algorithms to predict forest carbon stocks and fluxes. It includes K-nearest neighbors, artificial neural networks, random forests, support vector machines, and maximum entropy [25]. Remote Sensing: Remote sensing technology has become prevalent with the introduction of freely available Landsat data. Time-series analysis of medium-resolution satellite imagery provides detailed information on landscape changes over time. Intensive time-series analysis improves the quality and accuracy of remotely sensed data, expanding the types of surface changes that can be monitored. Several Landsat and Sentinel 2 satellites currently in orbit allow for the observation of forest carbon over large areas of the Earth every few days [26]. Atmospheric Inversion: This technique involves estimating carbon dioxide fluxes by measuring the concentration of CO_2 in the atmosphere and modeling its transport and dispersion. It provides a top–down approach to understanding carbon fluxes over large spatial scales.

To study the spatial and temporal characteristics of carbon dioxide fluxes in forest ecosystems, methods using remote sensing techniques can be primarily classified into two major categories. Indirect Estimation Methods: This includes estimating forest carbon stocks through the forest biomass method and determining the forest ecosystem carbon dioxide fluxes through changes in carbon stocks. These methods focus on monitoring forest carbon stocks to estimate the absorption or release of carbon dioxide. Direct Monitoring Methods: This involves monitoring using meteorological satellites or specialized CO_2 greenhouse gas observation satellites. These technologies directly observe the carbon exchange processes between forest ecosystems and the atmosphere.

To measure and monitor carbon dioxide fluxes more accurately, researchers have adopted several approaches, further divided into bottom–up methods, including dendrochronological and inventory methods, isotope methods, chemical flux methods, and box methods [27]. These methods estimate carbon fluxes by collecting data from the ground level, emphasizing detailed measurements at a local scale. Top–down measurements include remote sensing techniques, atmospheric inversion techniques [28], ecological modeling, and the eddy covariance method (EC) [29]. These methods use data collected from above or at a distance to estimate carbon fluxes on a larger scale, providing a macroscopic understanding of the carbon cycle in the entire ecosystem. Furthermore, these methods can also be categorized based on the timeliness of monitoring and real-time detection methods, such as the box method, EC method, remote sensing, isotope, chemical flux, and atmospheric inversion methods, that provide immediate data about the current state of carbon fluxes. Non-real-time Monitoring Methods, such as dendrochronological and ecological modeling methods, do not provide immediate data but are valuable for analyzing long-term trends. By reorganizing the content into more clearly defined groups and descriptions, this section is made clearer for the reader to understand the variety of monitoring methods and their applications.

In this paper, the monitoring of carbon sinks in forest ecosystems mainly refers to the above-ground part, and the standard methods, instruments, scope of application, and evaluation used to monitor forest carbon sinks are shown in Table 1. The methods, scope of application, and evaluation of forest carbon fluxes are shown in Table 2.

3. Ground-Based Remote Sensing

3.1. Methods of Observation

The sensor is on a ground platform such as vehicle-mounted, boat-mounted, handheld, fixed or movable elevated platforms, backpacks, and other wearables. Ground-based observation of forest carbon stocks can be carried out using traditional instruments for measuring DBH and tree height, optical measuring instruments, and new sample plot survey instruments, as well as the more brilliant Terrestrial Photogrammetry Technology (TPT), which refers to the technology of using a camera to take images of the object to be measured on the ground (within a range of 100 m), calibrate the images, and measure the size, shape and location of the object. TPT is a technology that uses a camera on the ground (within 100 m) to capture images of the object to be measured, calibrate the captured images, and measure the object's size, shape, and position. This technology works in a non-contact measurement mode, and the photogrammetry imaging of the target can be completed without the use of any specialized remote sensing platform, which has a wide range of applicability and is especially suitable for the measurement of objects in harsh environments or targets that are not easy to approach [30].

TPT includes telephotogrammetry, close-range photogrammetry (CPR), and aerial photogrammetry. Due to the varying degrees of missing canopy information caused by tree shading in forest stands and the limitations of computerized 3D modeling techniques and segmentation methods, the combination of sub-canopy CPR and TLS provides a solution for estimating the structural parameters of individual trees. Panagiotidis et al. (2016) [31] studied structure-from-motion accuracy using CRP in comparison with TLS to analyze DBH-height influence on error behavior. They found the lowest error (in point matching between the two different point clouds) near the ground. That also means that the error was negligible for all DBH estimations but not for the height, where the error was higher at higher stem portions (more significant error ~11 cm). That was mainly because of the inability of the camera during the alignment process to convert from 2D to 3D because of fewer matching points at that level. Of course, this depends on several parameters, like the latest technological advancements in hardware–software and the forest structure. The current state-of-the-art 3D scanning method for forestry is Terrestrial Laser Scanning (TLS), which was introduced to the field of forest mapping in the early 2000s [14], where the sensor calculates the distance of an object by analyzing the laser pulses it sends and receives, and which has been used to measure the height and diameter of trees [32]. This technology is characterized by high accuracy, wide acquisition range, and simple operation [33]. Close-up photogrammetry can also obtain tree measurement factors by taking images using smartphones [34]. The online simultaneous localization and mapping (SLAM) system was effectively implemented by Fan and his colleagues [35].

Ground-level forest carbon flux monitoring utilizes the EC, relaxed eddy accumulation (REA), box, and inventory methods. The most used instrument in carbon flux studies is the eddy covariance meter (Mobile Carbon Flux Platform) [36], and one of the most widely used methods is the eddy covariance method, which can be accurate down to 30 min and over periods of more than ten a. The EC method measures the exchange of CO_2 and other greenhouse gases between the atmosphere and the ecosystems by continuously sampling the air at a stationary point and measuring the change in the gas concentration. The EC method measures the exchange of carbon dioxide and other greenhouse gases between the atmosphere and ecosystems by continuously sampling air at a fixed point and measuring changes in gas concentrations [37]. Calculation of carbon fluxes is based on measurements of vertical wind speed, carbon dioxide concentration, water vapor, and other gases. EC is still limited to a few gases due to the need for faster response gas analyzers, high energy consumption, and low signal-to-noise ratio [38]. These problems have been solved by the advent of the REA technique, which is commonly used to measure the fluxes of various atmospheric tracers over ecosystems by collecting air from upstream and downstream air streams into separate tanks, reducing the need for fast-response analyzers. After collecting the air for a predetermined period, the slow-response analyzer analyzes the tracer gas concentration in the tanks to calculate the average flux [39]. The box method is commonly used to monitor GHGs in forest soils on a time scale of h-a. The box method is categorized into static and dynamic box methods, of which the static box method is one of the most commonly used. The inventory method, which is suitable for monitoring long-term changes in carbon fluxes at various scales, obtains standard wood biomass through destructive sampling and models biomass isokinetic growth with easy-to-measure variables, also known as the isokinetic growth method. Researchers used the EC and inventory methods to estimate carbon fluxes in upland mixed grasslands and seasonally flooded forests. The results showed that the estimates of carbon fluxes obtained by the two methods were essentially identical [40].

3.2. Impact of Seasonal Variations on Observation Equipment

The data's quality and completeness mainly depend on the measurement instruments used. The sensors could not acquire data on understory structure during the summer and fall due to canopy shading, which was not conducive to understory biomass measurements [41]; the advent of portable mobile observational instruments has facilitated the development of physiological and ecological studies of plant responses to global change by making it possible to move from indoor ex vivo analyses to field in situ in vivo measurements [42]. When observing temperate forests, the instruments are affected by seasonal changes, with lower temperatures in winter, mainly when working in mountainous areas, where the temperature decreases by 0.65 °C for every 100 m of elevation gain and where battery life and endurance of the instruments are the most significant problems. Close-up photogrammetry requires a linear laser transmitter and a camera with a source pixel sensor, which limits its use in daily practice, and the accuracy of the measurements may be affected by sunlight exposure. In natural environments, LiDAR signals are not stable enough, and the coded spot of the laser is easily covered by sunlight [34]. The classical exterior SLAM algorithm is highly dependent on lighting and texture, and its performance is severely affected when the ambient lighting changes or the scene lacks texture. Although the SLAM algorithm may be affected by the lack of sensor scale, extracting the sensor scale can improve the performance of the SLAM algorithm. Failure to remove depth information can lead to loss of map points and system initialization failure, while interference from dynamic objects, occlusions, reflections, etc., can degrade system performance [35]. When laser scanning and forest reconstruction are performed in dense forests, shadows can impede measurements and make volumes unobservable. When applying TLS in relatively dense forest stands, 25–30 m between laser scans and about 10–20 m from the ground is recommended to reduce seasonally induced measurement errors [33]. However, TLS is limited by line-of-sight obstacles and scanning angles and cannot capture information on the backside of objects. Moreover, segmenting a single tree and filtering out leaves, bushes, and depressions is necessary before reconstructing the tree structure from the point cloud [43]. Thus, TLS and ground-based LiDAR systems can work in tandem to acquire structural parameters of the upper and lower vegetation layers in forests with tall, dense trees.

4. Airborne Remote Sensing

4.1. Methods of Observation

Forest carbon sinks and stocks within the aerial observation area can be selected from both manned and unmanned platforms, which can carry various sensors, such as cameras, video cameras, LiDAR, hyperspectral imagers, microwave radar, and others. Unmanned Aerial Vehicle Lidar (UAV) and Airborne Laser Scanning (ALS) are often the ideal technical means to perform these tasks [44]. The UAV can carry a hyperspectral sensor (to identify tree species) [45], a visible digital camera (to identify tree height and biomass measurements) [46], a multi-spectral sensor (to identify canopy structure and determine attributes) [47], a thermal infrared camera (to identify canopy structure and determine attributes) [48], and LiDAR (to identify canopy structure, characteristics, and biomass delineation) [49]. UAV-based imaging can achieve satisfactory temporal, spatial, and spectral resolution compared to satellite and ground-based remote-sensing techniques [50]. UAV photography outperforms other imaging acquisition techniques when measuring objects from small to medium spatial scales [51]. Cameras mounted on uncrewed aerial vehicles should typically have a resolution of more than 10 megapixels and can capture still or moving images during daylight hours [52]. Photogrammetric techniques can also be combined with algorithms such as machine learning and neural networks to estimate carbon sinks or with various sensors for biomass and carbon sink monitoring [53].

ALS is an aircraft platform consisting of a laser scanner, a Global Navigation Satellite System (GNSS), and an inertial system [54], which is primarily used for the rapid acquisition of three-dimensional information on a regional scale [55]. ALS is an active remote sensing technique that utilizes laser pulses to measure the backscatter time and intensity of 3D targets on the Earth's surface [56]. However, LIDAR equipment has limitations such as high cost, large data volume, and susceptibility to weather and cloud cover. In contrast, Digital Aerial Photography (DAP) advantages are especially prominent at low and medium altitudes, with accurate colors in aerial images, distinct image texture features, high resolution, low cost, flexibility, efficiency [57], and the flexibility, efficiency, and low cost of DAP using UAVs as a mounting platform is well-suited for use in economically underdeveloped areas for use [58]. As a result, researchers often use LiDAR in combination with DAP to improve the accuracy of estimates [59]. The primary sensors for UAV detector gas piggybacking are the IR sensor, metal–semiconductor sensor, fluorescent sensor, electrochemical sensor, and EC, and EC is widely used [60]. Tethered balloons, fixed-wing UAVs, and rotary-wing UAVs are also widely used for monitoring low- and medium-altitude forest carbon fluxes [61]. Tethered balloons controlled by electric winches can carry sensing and sampling equipment for meteorological parameters and air pollutants. Still, their most significant limitations are their inability to maneuver and sensitivity to wind. Lightweight fixed-wing aircraft have the advantage of more excellent range and cargo capacity. However, their failure to hover and fly vertically and the potential for engine exhaust interference impose limitations on forest carbon flux measurements. Rotary-wing UAVs are more suitable for scientific research and civil flights due to their greater payload capacity and ability to transport a variety of instruments [62].

4.2. Impact of Seasonal Variations on Observation Equipment

Factors such as high cost and no-fly management policy for human-crewed aircraft have limited the popularization and application of large airborne LiDAR in forest resources survey and management [63]. With the development of low-cost UAV technology and the production of inexpensive LiDAR devices that can be mounted on small aircraft, opportunities have opened up for the development of relatively inexpensive Unmanned Airborne Laser Scanning (UAVLS). UAVLS has the potential to become a considerable airborne LiDAR complementary or alternative potential. However, small UAVs are light in mass and small in size, and in the windy season, the in-flight attitude is greatly affected by wind speed. The general surveying and mapping UAVs can withstand the effects of winds of less than five levels [64]. In addition, UAVs are demanding in terms of take-off and landing environments. Despite the availability of catapult equipment to reduce the difficulty of take-off, there are still specific site requirements for landing. The quality of images captured by optical cameras is more responsive to light and shadows in different seasons, such as in the tropics, where optical sensor data are unavailable due to cloud cover. For this reason, the solution proposed by the researchers is to develop UAV tilt photography, in which the UAV carries multiple cameras at different tilt angles to make up for the shortcomings of the traditional orthophoto that only contains image data from above and 3D reconstruction of the two-dimensional (2D) image through different angles to generate point cloud data ultimately. Compared to 3D laser scanning technology, UAV tilt photography can quickly and extensively acquire information on the top of the tree canopy. However, some challenges may be encountered during the measurement process, such as unbalanced piggyback platforms, scanner motion, harsh atmospheric conditions, and slope problems. However, uncertainty in spectral values, complex stand structure, shading caused by tall trees, and hyperspectral variation in the same vegetation type may also reduce the accuracy of the data. To overcome these problems, textured images or object-based methods can be considered for processing, which is expected to solve the above issues. UAVs also have limitations related to extreme conditions; airborne ash and debris can infiltrate the rotor blades of the UAV; high temperatures and hot air can damage equipment and limit flight altitude; high-speed air currents make it very difficult to pilot the UAV and increase the risk of losing or crashing the equipment, and sweltering weather conditions can affect battery performance [65].

Air humidity also significantly impacts the quality of the radiometric image; the higher the humidity, the greater the scattering of light. In response and in conjunction with real-time weather sites, the researchers have developed a dedicated smartphone application. This cell phone program can predict the optimal time for drone flights and display cloudiness percentages and rainfall probabilities. They can also measure the value of geomagnetic disturbances caused by solar activity [52].

5. Spaceborne Remote Sensing

5.1. Methods of Observation

Sensors on board spacecraft such as satellites, spaceships, space laboratories, etc. Integrating remote sensing technology with forestry surveys has enabled the observation of global forest carbon sinks [66]. The first is optical remote sensing, including MODIS, Landsat TM, Landsat ETM, Landsat OLI, SPOT, and Quick Bird, and the second is remote sensing microwave radar, which utilizes electromagnetic radiation in the microwave spectral range to collect data on the Earth's land, oceans, and atmosphere. Depending on the form of data used, they are classified as Synthetic Aperture Radar (SAR), Interferometric Synthetic Aperture Radar (InSAR), and Polarized Interferometric Synthetic Aperture Radar (PolInSAR). Then, there is LIDAR, categorized into waveform LIDAR and point cloud LIDAR, where waveform LIDAR is more advantageous than other forest resources in estimating forest structural parameters due to the high penetrating power of the laser pulses it emits. The laser pulses emitted are brilliant, giving waveform LiDAR an unparalleled advantage over other forest resource surveying techniques. Earth observation satellites such as ICESat, the Geoscience Laser Altimetry System (GLAS), GF-7, the Global Ecosystem Dynamics Investigation LiDAR (GEDI), the Land Ecosystem Carbon Monitoring Satellite (LECMS), and the Multiple Footprint Observation Satellite (MFOS) have all received LiDAR data from the ICESat), and other Earth observation satellites have received waveform LiDAR.

However, each of the three remote sensing monitoring techniques mentioned above has its limitations; Landsat, with its extensive archive of free data, has become an essential source of data for estimating biomass and carbon sinks; however, optical sensor data are suitable for retrieving horizontal vegetation structure, such as vegetation type and canopy cover, and are not ideal for estimating vertical vegetation structure. It is worth noting that some optical sensor data, such as Advanced Land Observing Satellite (ALOS), Panchromatic Remote Sensing Instrument for Stereo Mapping (PRISM), Terra Advanced Spaceborne Thermal Emission and Reflection Radiometer (Terra ASTER), and SPOT, have stereoscopic observation capabilities that can be used to determine the height of vegetation canopies, thereby improving the performance of biomass and carbon sink estimates. In contrast to the limitations of optical sensor data, SAR can penetrate the forest canopy to a certain depth, is sensitive to vegetation water content, and is not affected by weather, especially in areas where cloud cover makes it difficult to collect high-quality optical remote sensing data [67]. However, biomass estimation is complicated because radar data reflect the surface roughness of land cover rather than the differences between vegetation classes. Passive optical remote sensing techniques are plagued by critical issues such as signal saturation and algorithmic uncertainty, which limit the use of standard products derived from satellite imagery to detect subtle canopy cover changes, especially in dense tropical forests that are largely intact. Addressing the strengths and limitations of these three monitoring approaches, researchers have combined remote sensing data obtained from different methods to estimate forest carbon sinks [68].

Forest carbon fluxes were estimated using ecological modeling and atmospheric inversion methods [69], in which data were obtained from different carbon satellites. The Scanning Imaging Absorption Spectrometer for Atmospheric Cartography (SCIAMACHY) detector on ENVIronmental SATellite (ENVISAT) is the first onboard detector to use the short-wave infrared absorption band as the detection band. Based on SCIAMACHY, carbon monitoring satellites have been launched one after another to improve accuracy, such as Greenhouse gases Observing SATellite (GOSAT) found by Japan in 2009, Orbiting Carbon Observatory-2 (OCO-2) launched by the U.S. in 2014, GOSAT established by the U.S. in 2010, and GOSAT launched by Japan in 2011. OCO-2 was launched by Japan in 2009; OCO-2 was established by the U.S. in 2014, and the Chinese Carbon Dioxide Observation Satellite Mission (TanSat) was launched by China in 2016. All of these satellites in orbit are in the Earth's low orbit (LEO). Subsequent launches of China's meteorological satellites Fengyun-3D (FY-3D) (2017) and Gaofen-5 (2018) hyperspectral satellites, Japan's Greenhouse gases Observing Satellite-2 (GOSAT-2) (2018), the U.S. Orbiting Carbon Observatory-3 (OCO-3) (2019), and France's MicroCarb (2021) carbon monitoring satellites, considerably improved their detection accuracy, but their coverage and resolution are still problematic and unsuitable for monitoring carbon sources and sinks at regional or more minor scales. In addition, there is another class of carbon monitoring satellites mainly focusing on improving detection resolution and coverage through methodological and technological innovations, namely, the S5P satellite (Sentinel-5 Precursor) launched by the European Space Agency (2017), Sentinel-5 (2021), Geostationary Carbon Cycle Observatory (GeoCarb) (2022), China's Atmospheric Environment Monitoring Satellite (AEMS) (2021), High-precision Greenhouse gases Monitoring Satellite (HGMS) (2023), and the Franco-German Methane Remote Sensing LiDAR Mission (MERLIN) (2024) [70].

5.2. Impact of Seasonal Variations on Observation Equipment

Atmospheric conditions, to varying degrees, affect the satellite physical monitoring program. Under seasonal variations, clouds, aerosols, precipitation, and snowfall are the main factors affecting monitoring. Cloud cover is a necessary item in the image metadata information, and most data distribution platforms for optical satellite imagery use cloud cover as a basis for data screening [71]. Only a few types of images provide both cloud and cloud-shadow annotation information corresponding to the image, and the accuracy of cloud-shadow monitoring is low, with the widely used Fmask method of cloud-shadow monitoring only reaching about 70% accuracy [72]. Especially in the tropics, where only a few days of the year are cloud-free [71], monitoring of the surface by optical remote sensors is often hampered by clouds, especially in the Amazon Basin, where precipitation exceeds 2000 mm/year and where high-resolution radiometers (AVHRRs) and MODIS are unable to provide sufficient clear-sky observations over the Amazonian forest to generate reliable statistics to summarize vegetation dynamics. Although studies have proposed advanced atmospheric correction algorithms (MAIAC) that can increase clear-sky observations by a factor of 2 to 5 over traditional methods, clear-sky observations may still need to be available during critical composite cycles [73]. The presence of clouds and their cast shadows lengthens the cycle time for obtaining adequate full-coverage data over large surface areas, thus reducing the frequency of surface monitoring using remote sensing techniques. Since optical satellites are passive sensors, they can only collect meaningful imagery during daylight hours and, therefore, have a shorter potential revisit time than active sensors such as synthetic aperture radar or LiDAR, which poses a challenge for high-frequency remote sensing to monitor forest carbon sinks and fluxes. Cloudiness also affects sensor data collection, creating considerable data gaps in spatial and temporal domains. Dense cloud cover can completely disrupt the signal reflected by optical remote sensing and obscure the view of the surface below. Multi-spectral, multi-temporal, and recovery techniques are traditional techniques for reconstructing missing information in remotely sensed data. Multi-spectral methods apply to haze and thin cirrus clouds, where the optical signal is partially absorbed and partially reflected depending on the wavelength. The advantage of multi-spectral methods is that the information in the original scene can be utilized without additional data. However, these methods are limited to thin translucent clouds. Multi-temporal methods recover cloudy scenes by integrating information from reference images taken under clear skies. Multi-temporal methods are the most popular because they replace corrupted pixels with truly cloud-free observations. Researchers have recently begun utilizing powerful data-driven deep learning methods to solve the cloud cover problem [74]. Unlike dense clouds, thin clouds do not completely obscure the background so that background information can be recovered [75]. Globally, the average daily cloud cover over land, estimated from continuous observations by remote sensing satellites, is about 55 percent, with a distinct seasonal cycle. Therefore, methods for monitoring and masking clouds and cloud shadows are needed, including consideration of haze. The recent implementation of the Unmanned Aerial Hyperspectral Imaging System (UAV-HSI), which allows for the acquisition of ultra-high spatial and temporal resolution images at low altitudes below low-level clouds, provides new opportunities for optical remote sensing research [76].

Passive remote sensing is limited by daylight hours, cannot observe the daily cycle or high latitudes in winter, and will be affected by the interference of cloud cover and aerosols. Atmospheric aerosol is a multiphase system consisting of the atmosphere and a variety of solid or liquid particles suspended in the lower troposphere below 5 Km, in which the particle size is between 0.001 and 100 μm. Examples include soot, dust, sea salt, clouds, and precipitation particles. Aerosol optical thickness is most significant in the spring, second in the summer, and most minor in the fall and winter. Aerosols can directly affect solar radiation through scattering (sulfuric acid particles), which alters the number of cloud condensation nucleation particles and changes albedo and cloud lifetimes. The signal attenuation of the Normalized Difference Vegetation Index (NDVI) is also related to the atmosphere's aerosol content; the more turbid the atmosphere, the greater the attenuation. It has been shown that MODIS misclassifies large-scale dense aerosols as "clouds" in hazy weather [77]. In addition, some gas molecules in the atmosphere selectively absorb, scatter, and refract laser light, resulting in loss of laser light. Dramatic changes in the atmosphere's physical properties can lead to changes in illumination and scintillation. Atmospheric turbulence increases the chance of optical refraction. Transmission of the laser beam through turbulence leads to phenomena such as wavefront aberration, laser intensity scintillation, beam broadening, drift, etc., which reduces the laser beam's energy to reach the target, etc. All these factors degrade the performance of the LIDAR detection system.

6. Conclusions and Outlook

The innovation and application of forestry mapping equipment continue, and the data acquisition of forest ecosystems has gradually transformed from a rough and manual way to a precise and electronic direction. Relying on the background of GPS, RS, and GIS mapping technology, the precision forestry innovation system established through professional integration and innovation, combined with ecology, forestry, economic management, and intelligent technology, has promoted the development of global change ecology. The traditional instruments for measuring breast diameter and tree height are single-functioned on the ground scale. They cannot realize automatic data recording and saving, and adding optical measuring instruments has improved the precision and efficiency of single-tree mapping. On this basis, some new sample survey instruments have emerged that can collect multiple parameters of trees. With broad applicability, non-tact ground photogrammetry technology TPT is especially suitable for measuring objects such as targets in harsh environments or those that are not easily approachable. TLS is currently regarded as the most advanced 3D scanning method for forestry. The types of forest carbon flux monitoring instruments are few and fixed, and the instruments are mainly used to detect the concentration of CO_2. In the low to medium altitude range, UAVs can have multiple sensors. UAV-based imaging can achieve satisfactory temporal, spatial, and spectral resolution compared to ground-based instruments and satellite remote sensing techniques. Still, the measurement accuracy could be higher than that of ground-based instruments. In high-altitude monitoring, technologies based on optical remote sensing, microwave radar remote sensing, and laser radar remote sensing play a key role. Optical remote sensing technology has been widely adopted as a critical data source for biomass and carbon sink estimation due to the open and accessible nature of the data. Data quality may fluctuate due to data saturation and weather conditions. Optical sensors are mainly suitable for horizontal vegetation structures and cannot measure parameters such as vertical vegetation structures and canopy heights.

Fluctuations in particles such as temperature, light, wind speed, cloud cover, and aerosols caused by seasonal changes can significantly affect the physical observation process of mapping equipment and produce errors. Temperature changes can affect the range of the batteries in the instruments. Light from different seasons affects the image quality of optical cameras in photogrammetry and drowns out the coded spot emitted by the laser, resulting in a less stable LiDAR signal. UAV tilt photography solves this problem. The UAV carries multiple cameras to shoot at different tilt angles, which makes up for the shortcomings of traditional orthophotos that only contain image data from above and 3D reconstruction of 2D images through different angles, ultimately generating point cloud data. However, the attitude of small UAVs in flight is greatly affected by wind speed in windy seasons, and general surveying and mapping UAVs can only withstand the effects of winds below level 5. UAVs still have some significant challenges and limitations when faced with extreme conditions.

The presence of clouds and their cast shadows lengthens the cycle time for acquiring adequate full-coverage data over large surface areas, thus reducing the frequency of surface monitoring using remote sensing techniques. The number of clouds also affects the collection of data by the sensors, creating considerable data gaps in the spatial and temporal domains. Thick clouds can completely disrupt the reflective signal in optical remote sensing and hinder the observation of the surface below. Seasonal variations in aerosols interfere with remote sensing monitoring, with the optical thickness of aerosols being the most significant in the spring, followed closely by summer, and relatively low in the fall and winter. Not only can aerosols scatter solar radiation, thus affecting the propagation path of sunlight, but the presence of aerosols is directly related to the attenuation of the atmospheric NDVI signal, and dust in the spring of the Northern Hemisphere leads to a decrease in the value of NDVI. In addition, various atmospheric components, such as dust, smoke, rain, snow, and carbon dioxide, may interfere with the LiDAR detection system and affect its performance and accuracy. This paper comprehensively analyzes various measurement instruments employed at different research scales and their observation biases under other seasonal conditions. It aims to provide researchers with in-depth references and solutions. Researchers are expected to develop new observation instruments and algorithms while taking seasonal factors into full consideration to improve the accuracy and reliability of data further.

In the future of forest carbon sink monitoring technology, microwave remote sensing technology is further improved, with increasing resolution down to the sub-meter level, showing multi-polarization and multi-mode. The spatial resolution and spectral resolution of star-borne sensors have been greatly improved. Hyperspectral remote sensing and high spatial resolution remote sensing will be significantly developed; the integration of laser ranging and satellite positioning technology and video satellites makes 3D real-time imaging possible. The functions of professional image processing software are constantly being improved, such as the ability to read various data formats, the ability to process radar data, three-dimensional display and analysis, and compatibility with GIS software and databases. In terms of information extraction, fractal theory, wavelet transform, Artificial Neural Network (ANN), Genetic Algorithm (GA), morphology, Artificial Intelligence (AI), and other methods make information processing and analysis more intelligent and will be more closely integrated with GIS, GNSS, Data Processing System (DPS), AI, and Computer Vision (CV) and play a more significant role in various fields.

Based on the integrated remote sensing observation technology of "sky–space–earth" (Table 3), it can carry out integrated monitoring and assessment of multi-circle, multi-scale, multi-angle, and multi-detection media on a global scale, synchronously collect rich multi-source, multi-modal, and massive remote sensing data such as multi-spectral, hyperspectral, SAR, LiDAR, etc., and construct a remote sensing intelligent service cloud platform based on cloud architecture, big data, distributed storage/computing, artificial intelligence, and other technologies. In the future, based on cloud architecture, big data, distributed storage/computation, artificial intelligence, and other technologies, it will build a cloud platform for remote sensing intelligent services and unify the management, processing, analysis, release, and real-time sharing services to form an intelligent remote sensing cloud platform for collaborative observation, technology exchange, data sharing, facility networking, and other intelligent remote sensing platforms.

Table 3. Comparison of remote sensing platforms.

Property	Ground Platforms	Aviation Platforms	Space Platforms
Conceptual	Sensor on the ground	Remote sensing platforms suspended in the atmosphere (troposphere, stratosphere) below 80 km altitude.	Remote sensing platform located at an altitude of 80 km above sea level.
Functions and features	Close-range remote sensing, determination of spectral properties, and images of various features	Low-flight altitude, better ground resolution, maneuverability, less restricted by ground conditions, shorter cycle time, easy data recovery.	Macroscopic, integrated, dynamic, and rapid observation of the Earth. High-altitude sounding rockets are not limited by orbits, are flexible in their application, and are launched and recovered in a short period of time. They are costly and obtain little information. Spacecraft have large load capacity, can carry many kinds of instruments, timely maintenance, and convenient data recovery, but short flight time. The space shuttle is flexible and economical.

Table 3. *Cont.*

Property	Ground Platforms	Aviation Platforms	Space Platforms
Sensors on board	Geophysical spectrographic instruments, cameras, radars, etc.	Cameras, video cameras, LiDAR, hyperspectral imagers, microwave radar, and many other sensors.	Equipped with optical sensors, microwave sensors, etc.
Example	Tripod: 0.75–2.0 m; determination of spectral characteristics of various features, ground photography, scanning. Remote sensing tower: determination of fixed targets and dynamic monitoring; height of about 6 m. Mobile platforms: remote sensing vehicles, boats. Portable: wearable	Aircraft: Specially designed or converted from ordinary aircraft. Low-altitude aircraft: below 2 km above the ground, lower troposphere; helicopters can be as low as about 10 m. Medium-altitude aircraft: altitude of 2 km–6 km, middle troposphere High altitude airplane: altitude of 12 km–30 km Balloons: low-altitude balloons (troposphere), high-altitude balloons (stratosphere, 12 km–40 km)	High-altitude exploration rockets: generally at an altitude of 300 km–400 km, between airplanes and artificial Earth satellites. Spacecraft: Apollo; Gemini; Mir space station; Shenzhou series, etc. Space Shuttle: Columbia; Challenger; Endeavor; Discovery, etc. Artificial Earth satellites: Environmental satellites are categorized into three types according to their operational orbital altitude and lifespan: low-altitude short-lived satellite: altitude 150 km–350 km; life 1–3 weeks; high resolution; mostly used for military reconnaissance; medium-altitude long-lived satellite: altitude 350 km–1800 km; life expectancy of more than 1 year, such as land satellites, ocean satellites, meteorological satellites; high-altitude long-lived satellite: geosynchronous satellites or geostationary satellites with an altitude of 36,000 km, such as communication satellites and meteorological satellites.

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