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REVIEW ARTICLE

Remote sensing and machine learning based approaches in mapping coastal ecosystem and quantifying carbon stock

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Abstract

Blue carbon (BC) ecosystems involve mangroves, sea grasses and saltmarshes which are all influential coastal resources providing diverse environmental goods and services. These ecosystems play a pivotal role in the mitigating climate change impacts and global carbon cycle. On a large scale, it is challenging to monitor these ecosystems, which include time-consuming field measurements, but a remote sensing tool makes this monitoring more efficient by offering faster and broader coverage. This review focuses on how remote sensing utilized for mapping and monitoring BC ecosystems. Particularly multispectral and hyperspectral data, proves to be the most common method for mapping, Landsat time-series data are widely utilized for monitoring changes on larger scales. Despite the effectiveness of remote sensing, also challenges that persisted, including cloud coverage, spectral limitations and errors in microwave SAR data. Recent advances in multispectral imagery, SAR imagery, LiDAR data and pilotless aircraft, coupled with image analysis techniques, enhance the ability to quantify BC stocks at larger scales. However, challenges such as removal of atmospheric effect, water related issues and limitations in training samples hinder accurate estimation. This article gives an overview of use of remote sensing data to monitor BC ecosystem and quantify carbon stocks in those ecosystems. Despite challenges, the integration of multi satellite data fusion with machine learning techniques holds promise for advancing the accurate quantification of BC stocks.

Keywords: blue carbon; carbon ecosystem; carbon stock; mangroves; sea grasses; salt marshes

Introduction

The term "BC" describes the carbon that is released and sequestered by coastal ecosystems. Coastal ecosystems, including mangroves, sea grasses and salt marshes (collectively known as "BC" ecosystems) plays a crucial role in the global carbon cycle and provide numerous ecosystem services (1, 2). Carbon trapped within their above ground biomass, encompassing components such as dead wood, twigs and litter, as well as within their belowground biomass, including root structures of these ecosystem. Additionally, carbon is stored in non-living organic matter, such as litter, twigs and dead wood, over short-term (decadal) timescales, while sediments serve as long-term (millennial) carbon reservoirs (3). There are around 49 million hectares of BC ecosystems on Earth (4). Based on the BC sinks the rate of carbon sequestration varies considerably. The carbon burial rate in BC ecosystems may be influenced by a multitude of parameters including salinity variations, nutrient load (pollutant discharge), hydro cycle and suspended sediment delivery. These changes are influenced by a range of biophysical factors includes temperature, precipitation, sea level, nutrients, soil type and species assemblage (1). In comparison among all other ecosystems, mangrove, salt marsh and sea grass have relatively higher carbon burial rates in their sediments. In all three ecosystems, the rate of accumulation of carbon in sediment ranged from 18 to 1713 $gCm^{-2}yr^{-1}$. The amount of carbon accumulated in the tropical and temperate forests ranged from 0.7 to 13.1 $gCm^{-2}yr^{-1}$(1). These BC habitats have a far smaller area than the terrestrial forest, yet they sequester a greater amount of carbon overall than the terrestrial forest's carbon sink does. Despite having less aboveground biomass and a smaller geographic range, coastal biomes are still quite capable of having long-term sequestration of carbon in their sediments (5). However, these vital habitats are rapidly declining due to various anthropogenic pressures. Accurate and efficient monitoring of these ecosystems is critical for effective conservation and management strategies. Traditional field-based methods for mapping and quantifying carbon stocks are time-consuming, expensive and often limited in spatial coverage (6). Remote sensing, coupled with advanced machine learning techniques, offers a powerful alternative for large-scale, cost-effective monitoring (7). Numerous studies have explored the application of these technologies, but a comprehensive and up-to-date synthesis of their capabilities and limitations is lacking. This review provides a novel synthesis of the existing literature on remote sensing and machine learning applications for mapping and quantifying carbon stocks in coastal ecosystems. Unlike previous reviews that may have focused on specific ecosystem types or methodologies, this work offers a holistic perspective, integrating findings across various remote sensing platforms (e.g., multispectral, hyperspectral, LiDAR, SAR), machine learning algorithms (e.g., multivariate regression, SVM, XGB) and coastal ecosystem types (mangroves, seagrasses, salt marshes). Furthermore, we critically assess the strengths and weaknesses of different approaches, identify knowledge gaps and propose future research directions to improve the accuracy, efficiency and scalability of BC monitoring. This integrated approach will contribute significantly to the advancement of BC science and inform effective conservation policies.

Mangroves ecosystem

Mangroves are a highly specialised woody plants found in the intertidal zone of tropical and subtropical regions. Their salt resistance characteristics distinguish them (8). It has been calculated that there are around 152361 km^2 of mangroves worldwide (1, 9). Globally, Mangroves comprise under 1 % of tropical forests and cover less than 0.4 % of total forest. Twelve countries contain more than 65 % of the world's mangrove cover and Indonesia alone accounts for 20 % of it. True mangroves comprise about 70 species, 40 genera and 25 families under the groups *Rhizophoraceae* and *Avicenniaceae* (10) furthermore, a collection of mangrove associations coexists with freshwater and saltwater wetlands (10). Among all other coastal ecosystems, mangroves, sequestering around 226 ± 72 $TgCyr^{1}$ from the atmosphere and became most carbon rich ecosystem (11, 12). Their biomass and soils have the ability to store between 3100 and 4400 t of CO_2 ha^{-1}(13). Atmospheric carbon sequestration happens through living biomass (both aboveground and below ground), non-living biomass and sediments in the mangroves. Sediments are captured and stabilised by their vast underground and aboveground root systems. Numerous sources, including autochthonous sources (in situ carbon source), allochthonous sources (ex situ carbon source) contribute significantly to the carbon pool in sediments (14).

Sea grasses ecosystem

Sea grasses are entirely submerged, marine blooming angiosperm plants that thrive in shallow oceanic and estuary environments (15). It is one of the most crucial ecosystems and is home to several keystone species and aquatic species that are vital to life at all trophic levels (16). Although sea grasses constitute less than 0.2 % of the ocean's total surface, they are expected to bury around 27.4 $TgCyr^{-1}$. Sea grass has the ability to store carbon for millennia and has a carbon burial rate that is thirty five times quicker than that of tropical rainforests (17). It serve as a vital connection between mangroves and coral reefs by accumulating incoming sediments from the land (18). Additionally, it support fisheries, function as local indicators of water quality, control nutrient cycling, stabilise sediment and act as crucial carbon sequestrators, among other ecosystems (10, 19). Because of their strong root systems, sea grasses are able to withstand strong currents and waves on the sea's surface, especially during stormy seasons (20). Unlike mangroves and salt marshes, which are other types of coastal vegetation, sea grasses are entirely buried in shallow coastal water and may receive carbon through photosynthesis from dissolved carbon dioxide (CO_2) and bicarbonate (HCO^{3-}) in the water (21). Because of this unique characteristic, sea grasses play a unique function in carbonate chemistry by reducing the ambient partial pressure of CO_2, which lessens the effects of ocean acidification (22). Sea grasses, which founds in temperate, tropical and boreal parts of the world, belong to around 13 genera and 76 species and are an essential part of estuaries and coastal environments worldwide. Six of the 13 genera are mostly found in temperate regions, whereas the remaining seven genera are spread over tropical regions (20). These ecosystems are rather widely spread (>70 %) between the Tropics of Cancer and Capricorn. With over 25 % of the biosphere's sea grass cover, Southeast Asia has the largest proportion of sea grass cover. Other significant contributors include Western Africa (15 %) and North America (18 %) which share worldwide sea grass regions (23).

Salt marshes ecosystem

These are all low-lying, low-energy transition zones between emerging and submerged ecosystems, such as estuaries and deltas, where halophytic shrubs and herbaceous plants predominate rather than trees and also possessed with salt-tolerant rooted plants (24). Globally, salt marsh ecosystems are predominantly composed of species from the genera *Salicornia* (commonly known as glassworts) and *Spartina* (cordgrass). This ecosystem sustains the coastal food chain and add nutrients to the ocean (25). They are a vital ecosystem for the environment that gives many species an exclusive home that they cannot find in other places. The distribution of species in these habitats is influenced by a number of variables, such as elevation, tidal frequency and soil type (26). Due to its intricate and thick plant structure, it provides a secure environment for commercially valuable juvenile fish, prawns and shellfish. In addition to helping to control the quality of coastal water, salt marshes filter contaminants that are brought in from upland regions (5).

Factors influencing carbon sequestration in blue carbon ecosystem

Carbon sequestration in BC ecosystems is controlled by a variety of abiotic and biotic variables, including temperature, moisture content, biomass content, texture of the sediment, chemical composition of the litter and biomass quantity (27). Several additional factors such as shifting topography, shifting sea levels and increased erosion that reduces sediment aggregation also influences carbon storage. The carbon storage in BC systems is controlled by soil properties (mineralogy and texture), geomorphological settings (variation in landscape and hydrological) and biological output (primary productivity and remineralisation) (28). Plants in these ecosystems regulate carbon storage through nutrient cycling and biomass production, both are highly variable based on diversity of plant species and ecosystem specifics (29, 30). Mangrove and salt marsh ecosystems depend critically on nutrient exchange, salinity and precipitation (31). In contrast, sea grass ecosystems depend heavily on elements like species diversity, plant biomass and soil type, all are correlated with light penetration in waters (32). Moreover, the amount of allochthonous carbon that is transported and trapped can also be determined by hydrodynamics, river flow into estuaries and plant biomass (33).The biochemical composition of the organic matter, the rate at which soil accumulates and the textural characteristics of the soil all have an impact on how carbon accumulates and is preserved in the BC ecosystem (34). In addition to the natural factors, vegetation and sedimentary organic carbon stocks are significantly impacted by human induced activities such as aquaculture, deforestation and agricultural practices. Deforestation exposes sediments to leach out, leading to increase in microbial activity and accelerates nutrient cycle on the exposed sediment surface. Consequently, carbon that was previously preserved under anaerobic conditions is released through aerobic respiration, resulting in a decline in carbon stock (35).

Carbon cycle in blue carbon ecosystem

These ecosystems tend to acquire carbon from both locally generated and imported sources, both from terrestrial and marine, because they are located at the borders of land and water (36). The hydro period, water supply, geographical location and ecosystem productivity all affect the sources of carbon in coastal environments. Determining the sources of carbon is crucial when formulating the carbon budget for these ecosystems to differentiate deposited autochthonous carbon from allochthonous carbon (32).

Carbon that is generated and accumulates within the same location is classified as an autochthonous source of carbon. Consequently, organic matter derived from native vegetation, as well as benthic and epiphytic algae, along with phytoplankton, constitutes autochthonous carbon within coastal ecosystems (14). Through photosynthesis, all these native sources store CO_2 both from atmosphere and ocean and as biomass from plants, either above or below ground. This biomass was converted into litter, which will decay in the anaerobic environment that exists there and be deposited as sedimentary carbon in the ecosystem (34). The ecosystem's allochthonous carbon is created elsewhere and originates from other sources. These carbon sources may originate from marine or riverine material (such as floating phytoplankton or zooplanktons) and they may be deposited in various places from their source due to active hydrodynamic settings.

Coastal vegetation plays a pivotal role in sequestering carbon derived from both autochthonous and allochthonous sources within the sediment. Its intricate root systems also facilitate sediment deposition by capturing suspended particulate matter, thereby enhancing sedimentation processes (37). Due to anaerobic conditions, sediments have a low decomposition rate and maintain a significant amount of organic matter because of different autochthonous and allochthonous sources (13). In coastal ecosystems, the primary source of carbon is thought to be autochthonous sources. However, massive allochthonous carbon supplies are also received by coastal vegetation and these sources are just as important as autochthonous carbon sources. To properly assess the significance of mangroves, it is critical to illustrate the contribution of different carbon sources to the sedimentary storage. Both autochthonous and allochthonous carbon are buried in sediments that contain a significant amount of carbon that may be retained for millennia. They are therefore acting as a suitable carbon sink to mitigate the climate change impacts (38) (Fig. 1).

Mapping and monitoring of blue carbon ecosystem through remote sensing

It has been proven that remote sensing-based techniques are appropriate for mapping and tracking BC ecosystems (39, 40). They outperform conventional field based approaches in

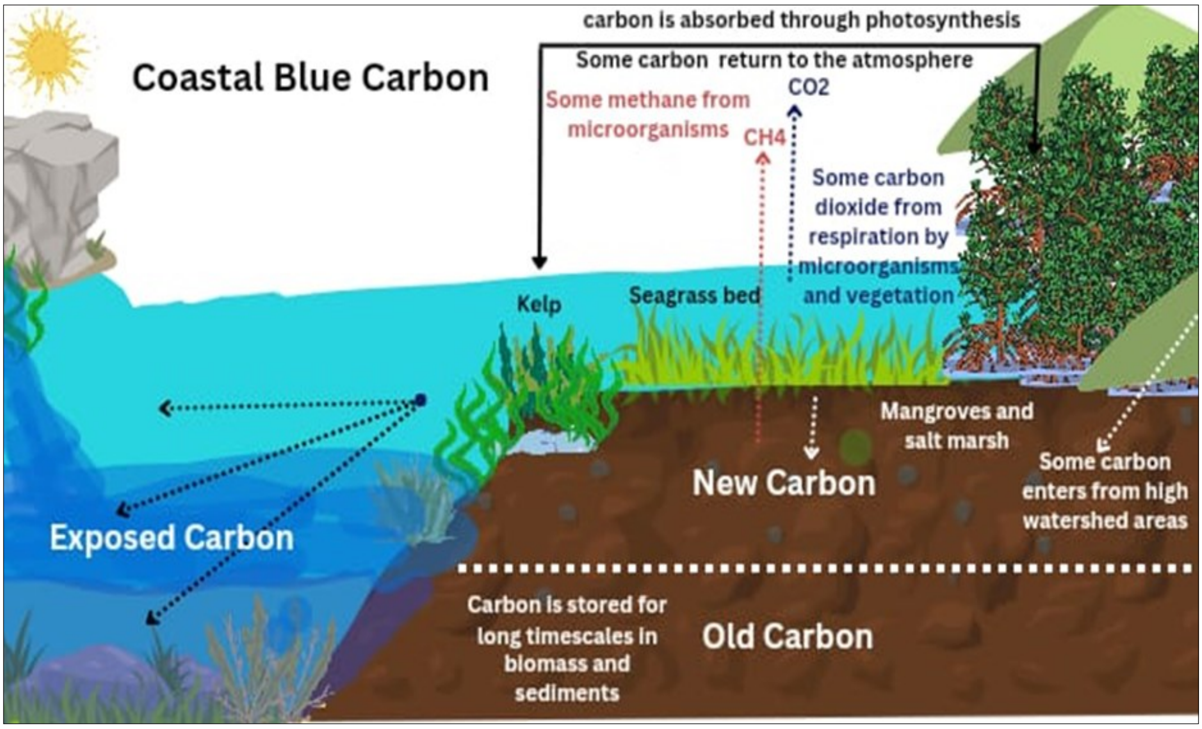

Fig. 1. BC ecosystem. Source: modified from NOAA (https://www.climate.gov/news-features/understanding-climate/understanding-blue-carbon).

terms of cost, accuracy, ease of repeating and coverage area (40). Nevertheless, cloud cover and the restricted availability of aerial datasets continue to be their drawbacks (41). These constraints can be addressed and new approaches to the development of more precise mapping techniques can be encouraged by the recent developments in computer vision, remote sensing and pattern recognition (42). Mapping and tracking BC ecosystems have seen a rise by applying machine learning techniques and integration of optical and microwave data in recent years. Several hyperspectral and multispectral sensors (both airborne and space borne), LiDAR and Unmanned Aerial Vehicle (UAV) platforms have been used in multiple research investigations to monitor BC ecosystem and its carbon dynamics (43). It is important to state that many satellite missions are no longer in operation, including Landsat-7, Hyperion and its predecessors, RapidEye, SPOT-4 and 5, as well as ALOS AVNIR-2.

Multispectral data for mapping and monitoring coastal ecosystem

The Landsat program represents the most pivotal series of multispectral satellites dedicated to land observation (44). Numerous studies in the field of environmental science have made use of Landsat data, including mapping flood susceptibility (45), forest change (46) and land use/land cover change detection (47). Multispectral data have become widely employed in many real world applications in recent years such as estimating carbon stocks (40). Finer spatial and temporal resolution satellite sensors, including SPOT, Quickbird, RapidEye, WorldView, IKONOS, OrbView and PlanetScope have been created because of the multispectral satellites growing progress. Recently, the improved spectral, temporal and spatial resolutions of optical sensors have facilitated their application in mapping and evaluating BC stocks within mangrove and salt marsh ecosystems (48, 49) employed Landsat imagery with spatial resolution of 30m to identify shifts in sea grass species in New Zealand. Landsat's intermediate spatial resolution (30 m) and temporal resolution (16-day repeat coverage) made it difficult to reliably estimate changing dynamics in the intertidal zones over time, even though it was capable to effectively predict long-term changes in sea grass cover. BC in salt marshes (50), sea grass meadows (51) and mangroves (52) has recently been extensively measured using Sentinel-2 MSI data. Using extremely high spatial resolution multispectral pictures from sensors like Worldview (2 m) and Planet Scope (3 m), study have been used to estimate the carbon stocks in coastal ecosystems(53). Interestingly, under the Planet and Research programme (https://www.planet.com/), users can access high resolution monthly images freely up to 5000 km^2. For instance, even in a tropical region of Vietnam with extensive cloud cover, mangrove aboveground biomass has been estimated by combining optical and microwave data *viz.,* ALOS-2, Sentinel-2and PALSAR-2 data (54). Similarly using the allometric relations and transfer coefficients, in salt marsh ecosystem conducted an assessment of aboveground biomass and its carbon stocks by integrating LiDAR and multispectral data (55). Their study focused on the salt marshes of West Galveston Bay, United States.

Hyperspectral data for monitoring coastal ecosystem

Hyperspectral sensors measure more continuous narrow spectral bands than multispectral imaging does. Typically, hyperspectral sensing uses a narrow bandwidth of less than 10 nm and a wavelength range of 380 to 2500 nm (56). Because of these enhanced features, hyperspectral imaging is more helpful than conventional multispectral data. Prior studies have indicated that the usage of hyperspectral data yields more precise estimates when monitoring mangrove biomass and its carbon stocks compared to the application of multispectral data (57). The accuracy of carbon estimates can be further enhanced by using hyperspectral sensors, which provide stronger signal-to-noise ratio and better spectral characteristics than multispectral data. However, compared to other data types, hyperspectral sensors like TianGong-1, EnMAP, PRISMA,DESIS, HISUI and HyspIRI have limitations due to their limited coverage (58). Still, the Hyperion sensor has been utilised in some research to measure the carbon stocks in mangroves and sea grass for past years (57).

Synthetic aperture radar in monitoring and mapping coastal ecosystem

Compared to optical remote sensing, SAR has several advantages. It uses active microwave to detect objects remotely (59), Sentinel-1A and 1B, ERS-1 and 2, ENVISAT, TerraSAR-X, ALOS PALSAR series, COSMOSkyMed and RADARSAT-2 are some of the most often utilised SAR sensors. They have been extensively employed for diverse applications, notably in the identification of urban structures (60), assessing land use/land cover (61) and the monitoring of deforestation and forest degradation (62). It is feasible to use SAR at various wavelengths also known as bands denoted in letter like Ka, C, S, L, K, Ku, X and P for different applications. For example, the X band with wavelength of 3.8 - 2.4 cm can be utilised to monitor canopy surfaces since they seldom ever pierce deeply into vegetation cover (63). Longer wavelengths such as the L-band, which is 24 cm are often used to quantify species structures since they may penetrate past leaves and into stems and branches (64). Both vertical (V) and horizontal (H) polarisations are often used with SAR sensors. Signals received in vertical polarisation and released in horizontal polarisation are indicated by HV. Targeted object features can be distinguished using various polarisations. For example, HV and VH polarizations exhibit the highest sensitivity to the foliage and branches within a forest canopy, while VV polarization is particularly responsive to surface roughness (65). Because of these features of SAR data, these sensors are becoming more and more common for quantifying mangrove ecosystems (66). For instance, showed how timeseries JERS-1 SAR and ALOS PALSAR datasets used to map the spread of mangroves. Since the energy of SAR band only goes a few centimetres into the water before being fully absorbed, SAR techniques are not frequently utilised to map submerged sea grasses since they may not be helpful for plant canopy under submerged condition (67). Due to the surface roughness induced by seagrass growth, certain intertidal seagrass populations located in low tidal zones can be effectively mapped using backscatter data obtained from Synthetic Aperture Radar (SAR) (68).

LIDAR for mapping and monitoring coastal ecosystem

Another active imaging technique in remote sensing is LiDAR that is light detection and ranging. This method can assess structure and plant height, from which the carbon stock of mangroves and salt marshes ecosystem can be derived. By using shorter wavelengths than in SAR, LiDAR varies from SAR (69). Bathymetric applications normally employ water-penetrating green light, whereas near-infrared light is frequently employed for terrestrial surface applications. By measuring the 3D structural profile of surfaces, a LiDAR sensor may replace 2D remotely sensed data. Other benefits include penetration of the tree canopy which preserves daylight, shading and relieve displacement (70). Although space borne LiDAR technology has increasingly been integrated into multi-sensor approaches for evaluating tree height and above-ground biomass. It is predominantly utilized in aerial platforms for such assessments (71). The biophysical characteristics of mangroves on the Thai coast using aerial LiDAR, demonstrating the potential use of LiDAR for calculating the height, location and individual tree crown's diameter in mangrove ecosystem (72). Space borne LiDAR is also useful for mapping BC. BC estimations in salt marshes and mangroves (40) have been achieved more often by using LiDAR (73). Worldwide mangrove canopy heights may be determined using ICE Sat/GLAS data (74) which in turn allows estimates of mangrove carbon stocks. The integration of NASA-funded Global Ecosystem Dynamics Investigation (GEDI) LiDAR with radar sensors has demonstrated improved precision in estimating canopy height within mangrove forests (75). However, LiDAR sensing has several drawbacks. For example, itis challenges in measuring individual crowns of dense tree precisely (72). By its limited sensitivity to submerged vegetation, tidal fluctuations and water levels, LiDAR data alone also fails to provide precise estimations of biomass and BC stocks within these ecosystems (76). Therefore, it is recommended to incorporate LiDAR alongside additional remote sensing datasets, including multispectral and SAR data, to achieve a more precise assessment of mangrove carbon (40).

Role of UAVs in coastal ecosystem monitoring

Unmanned Aerial Vehicles (UAVs) have been extensively utilized in remote sensing applications, particularly within the fields of agriculture, environmental sciences, LULC monitoring, risk assessment and soil organic carbon assessment (77). UAVs can serve as a platform for a variety of sensors such as lightweight LiDAR sensors and multispectral and hyperspectral sensors (78) and (79). UAVs has been extensively utilised in the field of coastal carbon due to the benefits. A novel method was created to generate the precision of monitoring Japan's sub-tidal and intertidal sea grass wetlands (80).

Several studies had been conducted to identify tree species, carbon stocks and mangrove above ground biomass (81, 82) by integrating ground observed data, space borne multispectral data and UAV imageries. There are a few drawbacks to using UAV based images for BC estimation, despite its possible advantages. For instance, at diverse species region, using the tree height (82, 83) identified a substantial disparity between data acquired through ground-based observations and that collected via UAV systems. A promising solution to this problem is to combine hyperspectral and laser scanning data with basic digital UAV system. Nevertheless, it is still expensive and difficult to integrate several super high resolution sensors (84).

Quantifying blue carbon

After acquiring data from either passive or active sensors, numerous steps in data analysis can be executed. Following sections provides an overview of current methods and their effectiveness in estimating BC remotely utilizing different satellite sensors and machine learning approaches.

Multivariate regression models

The BC ecosystem consists of both organic and inorganic carbon, sequestered within soil sediments, belowground biomass (BGB) and AGB (3). Traditionally, carbon content estimation involves point based field sampling followed by laboratory analysis, offering high accuracy but suffering from drawbacks such as time-consuming fieldwork and limited scale mapping (85). In recent years, there has been a shift towards quantifying the amount of BC storage using Earth Observation (EO) data in conjunction with on-site measurements as it is considered a cost-effective, reliable and highly scalable approach for mapping of BC in these ecosystems.

The estimation of above-ground biomass in mangrove ecosystems is conducted through the measurement of key biophysical attributes of mangrove species, including Tree Height (H), Diameter at Breast Height (DBH) and Canopy Diameter (CD) (54). The advancement of carbon retrieval methodologies necessitates the establishment of correlations between a restricted set of ground truth sampling points and remote sensing data, commonly achieved through the application of multivariate regression analysis. For example, (86) utilized the datasets of global mangrove from Global Mangrove Watch (https://www.globalmangrovewatch.org/) to perform mangrove carbon dynamics on a global scale. They observed a loss of carbon stock in mangrove over time, amounting to approximately 158 Mt, spanning the period from 1996 to 2016. Large scale canopy height data in Western Africa is employed to calculate biomass through allometric equations (87).

At local scales, methods like employing conversion factors for carbon content derived from biomass are common. Mangrove canopy height was mapped and estimated AGC stock using LiDAR and Landsat 8 OLI in Australia (88). In a similar way, carbon content of mangroves derived from biomass was estimated using NDVI data and regression technique from LISS IV multispectral satellite imagery (89).

Likewise, the LAI can be used to estimate AGC in sea grass in various climatic regions. Sea grass LAIs were determined using data from SeaWiFS (R^2ranges from 0.83 to 0.98) and SAMSON (with an R^2 value of 0.81) (90, 91). These LAI values were then utilized as input datasets for quantifying sea grass AGC through various empirical equations. These studies serve as notable examples illustrating the estimating BC stock indirectly through remote sensing data. The size of the sampling plot must be considered that can significantly impact the accuracy of regression outputs. This was evidenced by a study showing high accuracy in mangrove AGC estimation using Landsat-8 OLI (with R^2 ranging from 0.54 to 0.61) compared to Worldview-2 and ASTER VNIR images. Despite its relatively coarse spatial resolution, the pixel dimensions of Landsat were well-matched to the plot size within the study area, thereby facilitating the generation of a more precise carbon stock map (92). The carbon stock from mangroves of Pichavaram mangrove forest at Tamil Nadu for three years *viz.,* 2015, 2018, 2020 using Normalized Vegetation Index generated from the Landsat 8 OLI datasets (93). LiDAR has been employed for assessing carbon stocks in coastal ecosystem occasionally, in comparison to multispectral data, aerial imagery and hyperspectral data (55) employed simple linear regression models utilizing both multispectral aerial imagery and LiDAR data to estimate carbon stocks within saltmarsh ecosystems in West Galveston Bay, Texas, USA. However, these models exhibited relatively weak predictive performance, as indicated by R^2 values ranging from 0.28 to 0.47. Conversely, research conducted in a temperate mangroves in New Zealand reported a substantially stronger correlation between LiDAR-derived mangrove canopy height and field-measured AGC, attaining an R^2 value of 0.90 (94).

Blue carbon estimation through machine learning

Machine learning, as a nonlinear method of data processing, is adept at handling classification and regression tasks. It can be easily integrates with various types of spaceborne datasets, including multispectral, hyperspectral and Synthetic Aperture Radar (SAR) images (95). The machine learning models developed typically by incorporates input variables such as spectral reflectance of an object; vegetation indices obtained from multispectral or hyperspectral datasets and back scattered dB values obtained from SAR data. The field measured and remote sensing methods were combined for carbon stock estimation (96). The remote sensing-based approach utilizes NDVI, Photosynthetically Active Radiation (PAR) and Light Use Efficiency (LUE) as the key parameters for carbon stock estimation. To eliminate the atmospheric effects, 6S radioactive transfer model was employed for atmospheric correction. The statistical significance of the variation in NDVI values before and after atmospheric correction was evaluated using Student's t-test, which indicated a significant difference. The total carbon stock estimated at approximately 39.7188 t/ha. The reliability of the predictive methods and the validation of both approaches were substantiated through bias estimation, comparing carbon stock assessments derived from allometric equations and remote sensing techniques (R^2 = 0.964, bias = 0.915 %).

Machine learning algorithm utilizing the Hyperion obtained Enhanced Vegetation Index (EVI) and NDVI at a 30 m spatial resolution to accurately estimate mangrove AGC with an R^2 value of 0.87 (57). This research highlighted the potential of hyperspectral imagery in identifying mangrove species and estimating mangrove AGC. The precision of the estimation was contingent upon several factors, including the preliminary discrimination of mangrove species distribution, the accuracy of biomass quantification and the quantity of sampling locations employed for validation. Furthermore, texture attributes extracted from spectral reflectance have been extensively utilized as key input variables to model AGC in coastal BC ecosystems. Recently, SAR data such as ALOS-2 PALSAR-2 has been employed in carbon stock quantification in tropical mangrove areas using neural networks, demonstrated higher performance with an R^2 of 0.78 (97). Unmanned Aerial Vehicle (UAV) data has similarly been integrated with the Random Forest algorithm to estimate AGC in mangrove ecosystems, attaining a coefficient of determination (R^2) of 0.80. This model leveraged a diverse range of datasets, including tree height, vegetation indices and the co-occurrence matrix (98). In the United States, an effort to model AGC stocks in salt marsh ecosystems integrated multispectral data from Landsat-TM, ETM+ and OLI+ with Sentinel-1 imageries, employing random forest algorithms. Despite the incorporation of vegetation indices and dual-polari metric C-band SAR data into the machine learning framework, model performance remained suboptimal, with R^2 values ranging between 0.36 and 0.63. These findings shows that SAR sensors may have limited efficacy in estimating BC stocks within salt marsh environments. Conversely, a study conducted in the Skin flats and Caerlaverock salt marshes of Scotland applied decision tree models that integrated the NDVI from Sentinel-2 imagery alongside a Digital Terrain Model (DTM) to quantify Soil Organic Carbon (SOC) stocks. This approach demonstrated good results, with R^2 values of 0.59 to 0.80 (50).

Most recently, the above-ground carbon stock of mangrove ecosystems was evaluated within Komodo National Park, Indonesia by employing the XGBoost algorithm (52). Similarly, (51) employed data fusion technique with Sentinel-2 multispectral imagery and Sentinel-1 microwave datasets and incorporating optimization algorithms into the Categorical Boosting (CatBoost) framework to quantify organic carbon levels in seagrass beds. To estimate above-ground carbon in India's carbon-rich tropical mangrove forests, multispectral variables derived from Sentinel-1 and 2 data (99). This estimation was achieved through ensemble forecasting, leveraging multiple machines learning models, including Gradient Boosted Model (GBM), Random Forest (RF) and Extreme Gradient Boosting (XGB). Fundamentally, the optimization and selection of relevant features play a pivotal role in machine learning approaches, particularly when handling multiple model and multiple remote sensing datasets.

Challenges in estimating blue carbon

Ecosystem difficulties

BC ecosystems includes both terrestrial and submerged habitats. The estimation of AGC plays a pivotal role in quantifying the carbon stocks within these ecosystems. This assessment can be effectively conducted through the application of allometric equations derived from canopy height measurements (100, 101) and biomass (102), or through LAI data (103). However, retrieving below ground biomass and soil carbon presents greater challenges due to water column and soil layer, resulting in signal loss and diminished representation of habitat characteristics. In contrast to AGC retrieval, where spectral reflectance correlates well with amount of above ground carbon, quantifying below ground carbon or soil carbon necessitates an indirect approach due to the limited penetration of sensor signals into the sediment's top soil layer (104). In the case of sea grass ecosystems, the additional influence of the water column often requires studies to be conducted during low tide conditions when sea grass is exposed (48) or involves the application of various water column corrections (105).

Atmospheric and geometric effect

In multispectral and hyperspectral data, it is necessary to do atmospheric correction to remove the effects of sun glint, aerosols and water vapour content (106) and coastal wetlands ecosystem (107). Sun glint which involves the reflection of sunlight from the water surface, can significantly impact atmospheric noises in satellite or drone imageries, especially in BC ecosystems. It manifests as a bright spot on water surface images, leading to potential inaccuracies in estimating radiance existence from water during atmospheric correction. Sun glint has the potential to introduce an overestimation of radiance within the impacted region. Different techniques have been devised to evaluate the influence of sun glint on radiance readings and to rectify it during the atmospheric effect removal (2). Distinct methodologies for removal of atmospheric effects has been developed and continuously refined to suit specific environmental conditions, effectively addressing challenges associated with diverse settings such as inland water bodies within BC ecosystems, as well as turbid coastal waters in seagrass habitats (108, 109).

Need for higher resolution datasets

Estimates of BC are constrained by variations in spatial, spectral and radiometric resolutions across Earth Observation (EO) datasets. The Landsat mission, which includes sensors such as Landsat series operates with a 30 m spatial resolution. In contrast, Sentinel-2A and Sentinel-2B provide an enhanced spatial resolution of 10 meters (110). Landsat data are widely recognized as open-source resources frequently employed in the literature for evaluating BC dynamics. The latest advancement in this series, Landsat-9 OLI-2, offers an enhanced radiometric resolution, featuring 14 -bit quantization in contrast to the 12-bit resolution of Landsat-8 and the 8-bit resolution of Landsat-5 and Landsat-7. Additionally, both Landsat and Sentinel multispectral data incorporate Red-edge bands ranging from 704 to 783 nm, which play a pivotal role in the retrieval of BC estimates. Notably, recent studies demonstrated that red-edge based indices derived from Sentinel-2 imagery, exhibit exceptional sensitivity in assessing mangrove soil organic carbon (111).

Recommendations

It is recommended to integrate multispectral data and SAR data for assessing mangrove and saltmarsh ecosystems, while suggesting the use of multisource optical sensors for estimating BC in sea grass ecosystems. Due to the heterogenous nature of BC environments, adopting a universal approach for carbon stock estimation is not practical. Therefore, the fusion of EO data in Multimodal Learning (MML), Domain Adaptation Learning (DML) and Cross-Modal Learning (CML) forms is suggested. This strategy utilizes advancements in EO sensors to utilize various input datasets, capturing a range of local characteristics for quantifying carbon. Furthermore, the dynamic changes in BC ecosystem can be effectively assessed by integrating machine learning and deep learning techniques with high performance computing.

Conclusion

The integration of remote sensing and machine learning has transformed the mapping and monitoring of BC ecosystems by improving the accuracy, efficiency and scalability of carbon stock assessments. Traditional sensors like Landsat remain widely used, while the adoption of advanced platforms such as Sentinel-1 SAR, Sentinel-2 MSI, LiDAR, UAVs and hyperspectral systems has enhanced spatial and temporal resolution in estimating above-ground, below-ground and soil carbon stocks. Machine learning models including regression models, random forests, gradient boost and extreme gradient boost have demonstrated superior performance in biomass estimation and predictive carbon modelling, particularly when using multi-source and multi-temporal datasets. Integrating in-situ biomass measurements with satellite data using statistical and machine learning techniques has improved BC estimation, particularly for above- and below-ground biomass. To further enhance model accuracy, species-level classification is essential, especially given the limited availability of ground truth data. Challenges remain in mapping submerged vegetation like sea grasses, highlighting the need for tailored sensor fusion and improved classification methods. Emerging technologies such as semi-supervised and active learning, cloud platforms like Google Earth Engine and increased interdisciplinary collaboration are essential to address data limitations and support the development of robust, operational tools for BC quantification. These advancements are crucial for guiding conservation strategies, enabling carbon offset initiatives and reinforcing the role of BC ecosystems as vital carbon sinks in global climate mitigation.

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Authors' contributions

All the authors contributed equally to the conceptualisation of the work, interpretation, analysis, writing, reviewing and editing of the manuscript. All authors read and approved the final manuscript.

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