Science of the Total Environment 938 (2024) 173270

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

Review

Remote sensing-based mangrove blue carbon assessment in the Asia-Pacific: A systematic review

Abhilash Dutta Roy [a,b,c,d], Pavithra S. Pitumpe Arachchige [a,c], Michael S. Watt [e], Apoorwa Kale [c], Mollie Davies [c], Joe Eu Heng [a,c], Redeat Daneil [a,c], G.A. Pabodha Galgamuwa [a,c,f], Lara G. Moussa [a,c], Kausila Timsina [c], Ewane Basil Ewane [a,c,g,h], Kerrylee Rogers [i], Ian Hendy [j], Andrew Edwards-Jones [k], Sergio de-Miguel [l,m], John A. Burt [n], Tarig Ali [o], Frida Sidik [p], Meshal Abdullah [a,q,r], P. Pandi Selvam [s], Wan Shafrina Wan Mohd Jaafar [a,t], Isuru Alawatte [u], Willie Doaemo [c,v], Adrián Cardil [l,m,w], Midhun Mohan [a,c,g,o,t,x,*]

[a] Ecoresolve, San Francisco, CA, United States
[b] Mediterranean Forestry and Natural Resources Management, School of Agriculture, University of Lisbon, Portugal
[c] Morobe Development Foundation (via United Nations Volunteering Program), Lae, Papua New Guinea
[d] School of Agrifood and Forestry Engineering and Veterinary Medicine, University of Lleida, Lleida, Spain
[e] Scion, Christchurch, New Zealand
[f] The Nature Conservancy, Maryland/DC Chapter, Cumberland, MD, United States
[g] BlueForests, San Francisco, CA, United States
[h] Department of Geography, Faculty of Social and Management Sciences, University of Buea, Buea, Cameroon
[i] Faculty of Science, Medicine and Health, School of Earth, Atmospheric and Life Sciences (SEALS), Wollongong, NSW, Australia
[j] Institute of Marine Sciences, University of Portsmouth, Portsmouth, United Kingdom
[k] Plymouth Marine Laboratory, Plymouth, United Kingdom
[l] Department of Agricultural and Forest Sciences and Engineering, University of Lleida, Lleida, Spain
[m] Forest Science and Technology Centre of Catalonia (CTFC), Solsona, Spain
[n] Center for Interacting Urban Networks (CITIES) and Mubadala Arabian Center for Climate and Environmental Sciences (Mubadala ACCESS), New York University Abu Dhabi, 129188, Abu Dhabi, United Arab Emirates
[o] Department of Civil Engineering, College of Engineering, American University of Sharjah (AUS), Sharjah, United Arab Emirates
[p] Research Centre for Oceanography, National Research and Innovation Agency, Jakarta, Indonesia
[q] Department of Geography, College of Arts and Social Sciences, Sultan Qaboos University, Muscat, Oman
[r] Department of Ecology and Conservation Biology, Texas A&M University, College Station, TX, United States
[s] GAIT Global, Singapore
[t] Earth Observation Center, Institute of Climate Change, Universiti Kebangsaan Malaysia, 43600 Bangi, Selangor, Malaysia
[u] Department of Forest Conservation, Ministry of Wildlife and Forest Resources Conservation, Sri Lanka
[v] Department of Civil Engineering, Papua New Guinea University of Technology, Lae, Papua New Guinea
[w] Tecnosylva, León, Spain
[x] Department of Geography, University of California - Berkeley, Berkeley, CA, United States

* Corresponding author at: Department of Geography, University of California - Berkeley, Berkeley, CA 94709, United States.
E-mail address: mikey@ecoresolve.eco (M. Mohan).

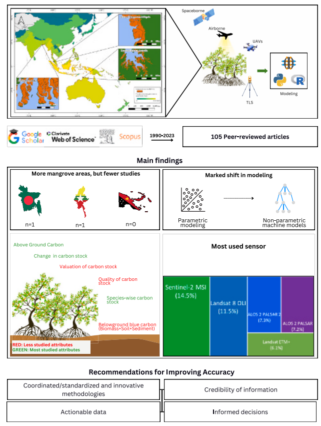
https://doi.org/10.1016/j.scitotenv.2024.173270

Available online 19 May 2024

HIGHLIGHTS

- The potential of remote sensing in assessing blue carbon needs further exploration.
- Fewer studies from mangrove-rich countries (Myanmar, Bangladesh, and Papua New Guinea)
- Sentinel-2 MSI (14.5 % of overall usage) was the most used sensor.
- Research on below-ground carbon and valuation of carbon stock is limited.
- Improvement in accuracy and precision based on innovative methodologies is needed.

GRAPHICAL ABSTRACT



ARTICLE INFO

Editor: Yuyu Zhou

Keywords:
Above-ground mangrove biomass
Mangrove carbon
Coastal ecosystems
Indo-Pacific
Machine learning
Multispectral sensors

ABSTRACT

Accurate measuring, mapping, and monitoring of mangrove forests support the sustainable management of mangrove blue carbon in the Asia-Pacific. Remote sensing coupled with modeling can efficiently and accurately estimate mangrove blue carbon stocks at larger spatiotemporal extents. This study aimed to identify trends in remote sensing/modeling employed in estimating mangrove blue carbon, attributes/variations in mangrove carbon sequestration estimated using remote sensing, and to compile research gaps and opportunities, followed by providing recommendations for future research. Using a systematic literature review approach, we reviewed 105 remote sensing-based peer-reviewed articles (1990 - June 2023). Despite their high mangrove extent, there was a paucity of studies from Myanmar, Bangladesh, and Papua New Guinea. The most frequently used sensor was Sentinel-2 MSI, accounting for 14.5 % of overall usage, followed by Landsat 8 OLI (11.5 %), ALOS-2 PALSAR-2 (7.3 %), ALOS PALSAR (7.2 %), Landsat 7 ETM+ (6.1 %), Sentinel-1 (6.7 %), Landsat 5 TM (5.5 %), SRTM DEM (5.5 %), and UAV-LiDAR (4.8 %). Although parametric methods like linear regression remain the most widely used, machine learning regression models such as Random Forest (RF) and eXtreme Gradient Boost (XGB) have become popular in recent years and have shown good accuracy. Among a variety of attributes estimated, below-ground mangrove blue carbon and the valuation of carbon stock were less studied. The variation in carbon sequestration potential as a result of location, species, and forest type was widely studied. To improve the accuracy of blue carbon measurements, standardized/coordinated and innovative methodologies accompanied by credible information and actionable data should be carried out. Technical monitoring (every 2–5 years) enhanced by remote sensing can provide accurate and precise data for sustainable mangrove management while opening ventures for voluntary carbon markets to benefit the environment and local livelihood in developing countries in the Asia-Pacific region.

1. Introduction

1.1. Background

Mangrove forests provide a variety of ecosystem services and functions including habitats for a wide variety of benthic macrofauna (shrimps, crabs, mollusks), shoreline stabilization, bioremediation, food provision, honey, timber, fuelwood, tannins, waxes, and avenues for sustainable ecotourism (Mukherjee et al., 2014; Dahdouh-Guebas et al., 2021). In addition to these services, mangrove forests provide potentially scalable and cost-effective natural climate-change solutions with a global above- and below-ground carbon stock of 1.6 Pg and 10.2 Pg, respectively (Alongi, 2020; Kauffman et al., 2020; Macreadie et al., 2019). This fraction of organic carbon stored in mangrove ecosystems is referred to as mangrove blue carbon (Macreadie et al., 2019) and remains trapped for long periods (centuries to millennia). The term 'blue carbon' was coined by Nellemann et al. (2009), to differentiate coastal ecosystems from the 'green carbon' of terrestrial forests. Blue carbon sequestration can aid in mitigating CO_2 emissions from land-use change, especially in countries with large coastlines (Taillardat et al., 2018). The role of mangrove ecosystems in climate change mitigation is more significant in the tropical coastal region and effective at the national and regional scale compared to the global scale (Alongi, 2020; Taillardat et al., 2018).

Notwithstanding the significant volume of stored carbon, mangrove forests also play a significant role in climate change adaptation by stabilizing coastal lands through their complex structure and in areas that permit, landward accretion of organic build-up, which significantly reduces the impact of sea level rise (Gijsman et al., 2021). Rates of biodegradation of the large woody detritus (LWD) are quicker in mid- to low-intertidal zones (< 1 year) whereas it can take many years in high-intertidal zones. Therefore, if geomorphology does not permit landward accretion with rising sea levels, belowground carbon storage values could significantly decline (Hendy et al., 2022).

The Asia-Pacific region accounts for 50.6 % of the global mangrove extent (147,359 km^2) (Bunting et al., 2022). Despite this, the region has been identified as a global hotspot of mangrove deforestation due to anthropogenic activities such as aquaculture, agriculture, and urbanization (Bunting et al., 2022; Richards and Friess, 2016). From 1996 to 2020, a loss of 3329 km^2 or 4.3 % of mangrove areas was reported in the

Asia-Pacific region (Bunting et al., 2022), which took place mainly in Indonesia, Myanmar, Malaysia, Philippines, Thailand, and Vietnam (Goldberg et al., 2020). This highlights the need for continuous monitoring to inform remedial action.

Accurate measuring, mapping, monitoring, and modeling of mangrove ecosystems subsequently support informed decision-making for policy formation and regulations for the sustainable management of mangrove ecosystems. These measures are particularly vital for prioritizing locations that need immediate attention, so they can continue to support local livelihoods while contributing toward resilience to climate change. Between the late 20th and early 21st century, the rate of global loss in mangrove extent decreased from 2 % to <0.4 % per annum, which was due to improved monitoring, management, rehabilitation and protection, changing industrial activities, recognition of its significance, community-based involvement, and inaccessibility of remaining intact mangrove forests (Friess et al., 2016). In the Asia-Pacific region where mangrove ecosystems are scattered mostly in ecologically and socio-culturally complex areas, sustainable management decisions based on robust data collection using non-invasive methods such as remote sensing can be very useful.

Remote sensing tools can help identify and efficiently quantify above-ground mangrove carbon stocks in a more robust manner (Pham et al., 2019). Multitemporal satellite imagery, integration of multispectral and Synthetic Aperture Radar (SAR), and airborne Light Detection and Ranging data (LiDAR) have been proven to be successful in mapping mangrove ecosystems due to their low cost, high accuracy, and ability to map larger areas compared to field-based methods (Hossain et al., 2015; Pham et al., 2019; Rondon et al., 2023). The return frequency of satellite data facilitates continuous mapping, monitoring, and assessment of mangrove blue carbon. Different attributes of mangrove blue carbon can be efficiently quantified from satellite and airborne sensors that cover large spatial extent and have automated data processing methods. Through linking remotely sensed data with field-based measurements, blue carbon estimates can be scaled to larger spatial extents. Recent advancements in remote sensing techniques in combination with machine learning and deep learning models can provide more accurate results while mitigating the limitations caused by limited airborne data and cloud cover (Pettorelli et al., 2017). The emergence of Unmanned Aerial Vehicles (UAVs) in recent years has allowed for the mapping of mangrove forests at high resolution facilitating informed conservation decisions at local-scale and at locations where satellite or airborne data is either insufficient or unavailable.

1.2. Aims and contribution of the study

There has been a considerable amount of research in the Asia-Pacific region focusing on mangrove blue carbon that integrates remote sensing and modeling methods. However, previous reviews of the region have often lacked a systematic approach for compiling information that describes the chronological order of research and assesses the trends using a holistic approach. Key milestones in remote sensing-based mangrove blue carbon estimation, variation in mangrove blue carbon captured by remote sensing, challenges, and opportunities focused on the Asia-Pacific region have not been well documented. Therefore, the aims of this study were to 1) identify trends in sensors and modeling approaches and their chronological development in estimating mangrove blue carbon in the Asia-Pacific, 2) assess the attributes of mangrove blue carbon estimated by remote sensing, 3) characterize the variation in mangrove blue carbon sequestration estimates found using remote sensing, and 4) identify research gaps, challenges, and opportunities to improve the estimation of mangrove blue carbon and to provide recommendations. Our systematic review identifies the contribution of remote sensing in measuring mangrove blue carbon in the Asia-Pacific region while highlighting the latest approaches for enhancing the accuracy and efficiency of mangrove blue carbon estimations.

2. Methods

2.1. Study area

The Asia-Pacific region is classified into four sub-regions: East Asia, South Asia, Southeast Asia, and the Pacific Ocean. This region is known to have the highest mangrove species diversity in the world and accounts for 50.6 % of global mangrove cover (74,506 km^2). The highest mangrove cover occurs in Indonesia (29,534 km^2), followed by Australia (10,171 km^2), Myanmar (5435 km^2), Malaysia (5246 km^2), Papua New Guinea (4525 km^2), Bangladesh (4484 km^2), and India (4038 km^2). The 13 Pacific islands together amount to 5716 km^2, and Papua New Guinea, Solomon Islands, and Fiji are the main contributors (Fig. 1). The greatest losses in mangrove areas from 1996 to 2020 have occurred in Southeast Asia, which lost 2457 km^2 (4.8 %) of mangroves, driven by commodities development, and in particular aquaculture (Bunting et al., 2022).

This region harbors approximately 75 % of the global true mangrove species ($n = 68$; SI Fig. 1). Notably, Indonesia has the most diversity with 45 species, followed by Malaysia with 36 species, and Thailand with 35 species (Suratman, 2008).

2.2. Data collection

In this study, a systematic literature review on "Measuring mangrove blue carbon using remote sensing in the Asia-Pacific" was carried out following Preferred Reporting Items for Systematic Reviews and Meta-analysis statements (PRISMA) (Moher et al., 2009) in alignment with the PICOS (Population, Intervention/Exposure, Comparator, Outcome, and Study design) approach (Badzmierowski et al., 2021). The search expressions and the workflow are presented in Table 1 and Fig. 2, respectively.

Our literature search process used online databases (Scopus and Web of Science) and a search engine (Google Scholar) to gather sources published between January 1990 and June 2023. For Google Scholar, we used a Python-based automated literature review where the first hundred Google Scholar page results were considered (https://serpapi.com/search?engine=google_scholar). The primary list of articles included 2055 results, of which 229 were removed after filtering for duplicates. During the first phase of screening, relevant search results were identified based on the title and abstract considering the eligibility criteria, followed by full-text verification during the second phase of screening. Articles not explicitly mentioning "Asia-Pacific" or its constituent regions, "mangrove" or "remote sensing" were excluded from the analysis (Table 1). Non-English articles, gray literature (conference proceedings, book chapters, reports), and reviews were also excluded. Disparities that arose during the full-text review on inclusion/exclusion decision-making were carefully examined and resolved. Then, a comprehensive search was conducted by identifying relevant articles in the reference list of the final set of articles using citation networks and complementary searches in a backward and forward snowballing approach (Badzmierowski et al., 2021). The data required for this study was extracted from the final list of articles (i.e., journal and year of publication, study location, remote sensing platform, sensors, modeling approaches and statistics, main purposes of the study, mangrove carbon-related attributes and variation estimated by remote sensing, data reported on carbon sequestration for different mangrove species and in different countries/locations, research gaps/challenges/opportunities highlighted by authors, etc.)

2.3. Data analysis

The aforementioned extracted data were analyzed and presented as figures, and tables (i.e., number of articles published in each year, country-wise remote sensing-based publications, the timeline of the usage of sensors/modeling approaches, model performance statistics, mangrove carbon-related attributes estimated by remote sensing,

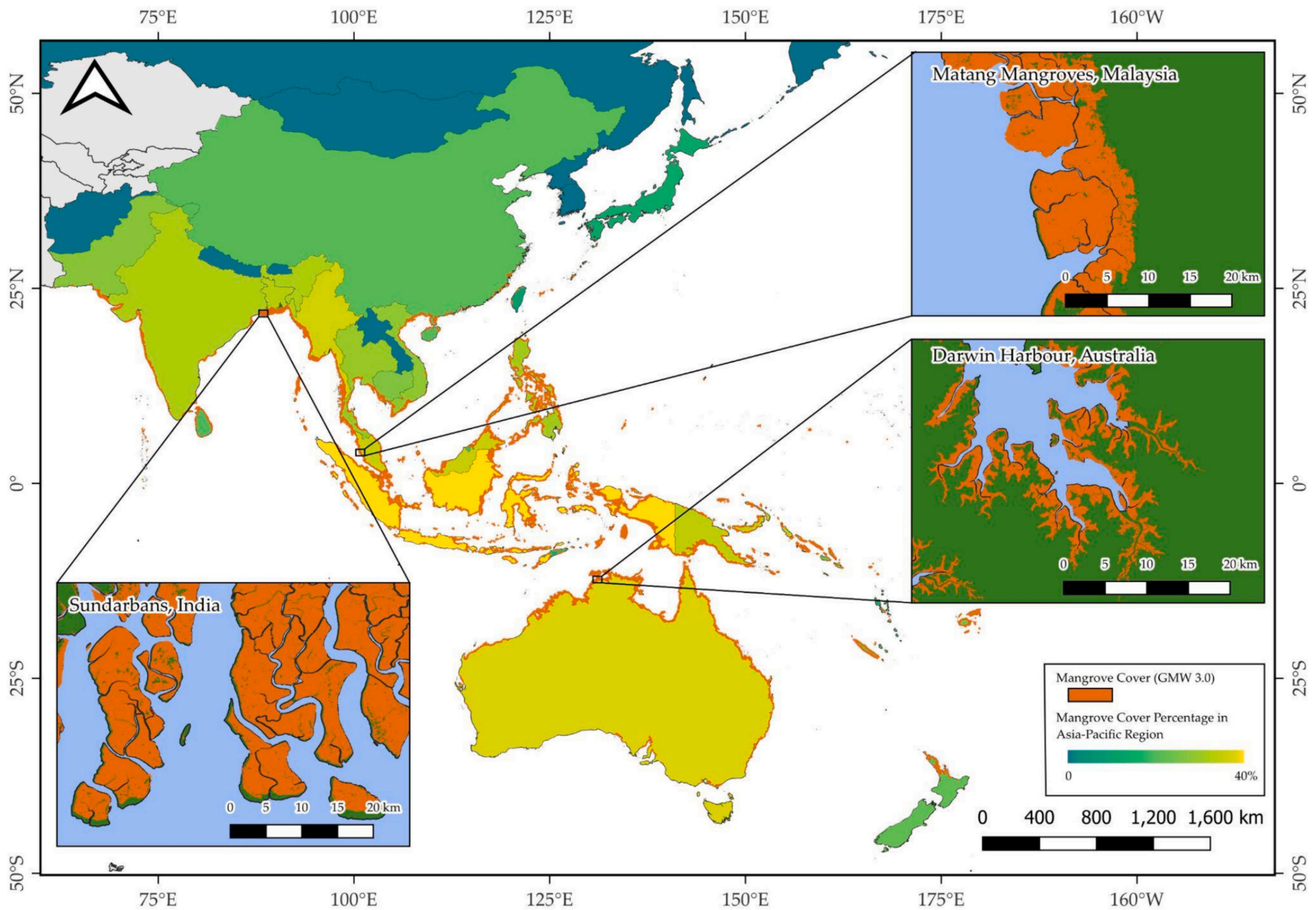


Fig. 1. Distribution of mangroves in the Asia-Pacific region (2020) determined by Global Mangrove Watch 3.0 data.

Table 1
Search expressions used to collect literature.

Criteria	Search expression
What	("Mangrove blue carbon" OR ("mangrove"AND ("blue carbon" OR "carbon"OR "biomass"OR "canopy"OR "stock"OR "forest structure" OR "restoration"OR "threats"OR "litter")))
AND	("Asia-Pacific" OR "Indo-Malayan" OR "Australasia" OR "South Asia" OR "Southeast Asia" OR "Indonesia" OR "Australia" OR "Malaysia" OR "Myanmar" OR "Bangladesh" OR "India" OR "Thailand" OR "Vietnam" OR "Cambodia" OR "Sri Lanka" OR "Singapore" OR "Papua New Guinea" OR "New Zealand" OR "Pacific Island" OR "Pakistan" OR "China" OR "Japan" OR "Philippines" OR "Fiji" OR "Kiribati" OR "Brunei" OR "Maldives" OR "Taiwan" OR "Tonga" OR "French Polynesia" OR "New Caledonia" OR Timor-leste OR Micronesia OR Melanesia OR Polynesia OR Tuvalu OR "Hong Kong" OR "Samoa")
How	("Remote Sensing" OR "LiDAR" OR "Satellite image*" OR "aerial image*" OR "GIS" OR "Drone" OR "UAV" OR "SAR" OR "hyperspectral" OR "multispectral" OR "UAS" OR "earth observation" OR "EO" OR "mapping" OR "radar" OR "Thermal" OR "ALS" OR "Light detection and ranging")
When	January 1990 to June 2023

variation of mangrove blue carbon captured through remote sensing). Research gaps, challenges, and opportunities related to mangrove blue carbon measurement in the Asia-Pacific region were compiled from information extracted from the reviewed articles. We also compiled recommendations provided by authors in reviewed journals along with our insights to provide guidance for future research endeavors and to facilitate informed decision-making, and policy recommendations.

3. Overview of the final list of articles

A total of 105 articles were selected from the systematic screening, which were published in 62 peer-reviewed journals sourced from various publishers. These journals included Remote Sensing (10 articles), Forests (5 articles), International Journal of Remote Sensing (5 articles), Remote Sensing of Environment (5 articles), Journal of Applied Remote Sensing (3 articles), Remote Sensing Applications: Society and Environment (3 articles), with the remainder distributed among others (See Supplementary Material Table S1 for further details).

To understand the interrelation of conceptual domains within the selected articles, a cluster analysis of the co-occurrence data of keywords from the selected articles was made (Piao et al., 2023). The VOSviewer software (v 1.6.20) was adopted to elaborate and visualize the co-occurrence networks of each keyword cluster. See SI Fig. S2 and SI Table S2 for the keyword cluster map and keyword frequency of occurrence, respectively.

4. Spatio-temporal distribution of the reviewed articles

During 1990–2023, 105 peer-reviewed English articles were published on the estimation of mangrove blue carbon in the Asia-Pacific region. The first peer-reviewed article on remote sensing-based mangrove biomass estimation in the Asia-Pacific was published in 2007 (Li et al., 2007) and the number remained below five papers per year through 2013 (Fig. 3). From 2014 through 2022, there was a significant increase in the number of peer-reviewed articles published in English, the highest number of publications occurring in 2020 (Fig. 3). This could be attributed to the increase of openly accessible remotely

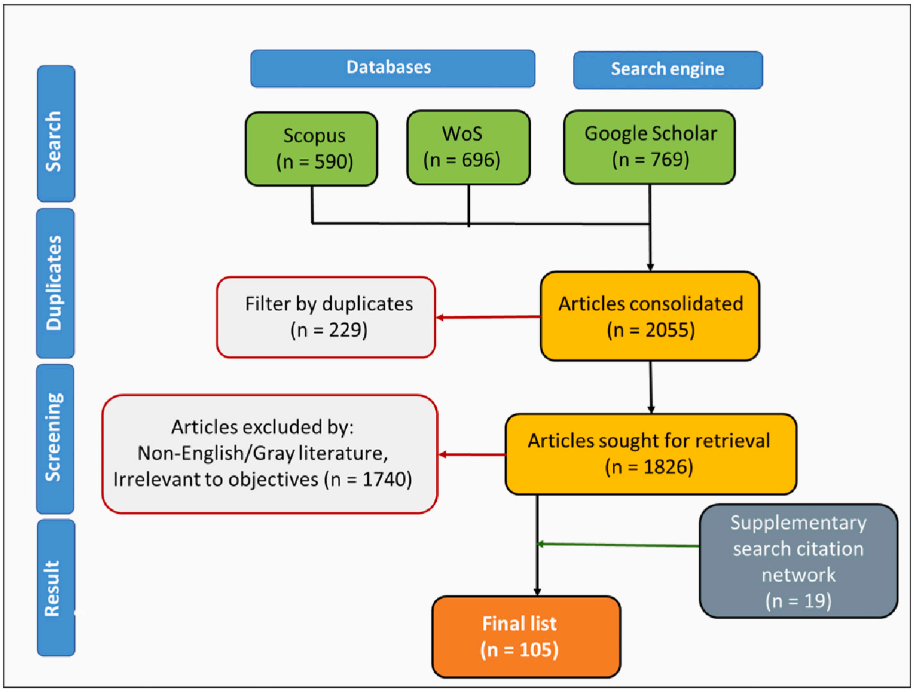


Fig. 2. Workflow representing the systematic literature review process.

sensed images and greater computational power over the years.

With respect to the study location in the screened articles, Indonesia led the list by contributing 26 articles (Fig. 3). China followed with 22 articles, Vietnam with 19 articles, India with 12, Australia with 8, while Malaysia had 9 (Fig. 3). Moreover, Thailand contributed 4 articles, and the Philippines 3. Bangladesh, Brunei, Myanmar, Cambodia, Singapore, New Zealand, and Sri Lanka have 1 article each. Global studies were not considered when determining country-wise statistics.

Our systematic review showed there were very few research publications from Myanmar, Bangladesh, and Papua New Guinea ($n = 0$) despite the high mangrove area. In contrast, China has published 22 articles even though the area of mangroves in China is far less (Fig. 1. and Fig. 3). This highlighted the significant contribution of countries with higher nominal Gross Domestic Product (GDP) to the remote sensing-based mangrove blue carbon research (i.e China- 17,700 billion USD) than other countries (Myanmar-74.8 billion USD; Bangladesh-446.3 billion USD; Papua New Guinea-31.7 billion USD) (IMF, 2023). Countries without publications, but with high areas of mangroves, may also have limited accessibility to advanced and emerging high-resolution remote sensing technologies which might not always be openly accessible.

5. Sensors used for measuring mangrove blue carbon during 1990–2023

Among the different types of sensors used in the reviewed literature, spaceborne sensors were most commonly used, featuring in 85.5 % of the reviewed articles. Drone/UAV platforms, that were able to capture fine-scale data and provide better spatial resolution for targeted observations, accounted for 7.9 %, while airborne platforms were used in 4.2 % of the reviewed articles (Fig. 4). Terrestrial remote sensing platforms contributed to 2.4 %, supporting ground-based observations and validations. With respect to sensor types, multispectral sensors (59.3 %) dominated, followed by radar (28.1 %), LiDAR (10.8 %), and hyperspectral (1.8 %) sensors.

Sentinel-2 MSI was identified as the most preferred sensor, accounting for 14.5 % of overall usage (Fig. 4). Then, Landsat 8 Operational Land Imager (OLI) (11.5 %), ALOS 2 PALSAR 2 (7.3 %) and ALOS PALSAR (7.2 %) have also been used frequently for studying mangrove blue carbon followed by Landsat 7 ETM+ (6.1 %), Sentinel-1 (6.7 %), Landsat 5 TM (5.5 %), UAV LiDAR (4.8 %), SRTM DEM (5.5 %), airborne LiDAR (3 %) and multispectral UAV (3 %) (Fig. 4). Aerial photographs have also been used in some earlier studies. Many studies have used more than one remote sensing platform and incorporated a data fusion approach, and we provided equal weighting to each sensor when calculating statistics. Supplementary material Table S3 contains a detailed summary of all the sensors used for measuring mangrove blue carbon in the Asia-Pacific from 1990 to 2023.

The European Space Agency (ESA) Sentinel-2 has been widely used for measuring mangrove blue carbon since its launch in 2015 (Fig. 4). The MultiSpectral Instrument (MSI) captures imagery in 13 spectral bands and its five-day revisit frequency with sensors 2-A and 2-B are useful for quick monitoring of mangrove ecosystems. The first study that used Sentinel-2 for estimating mangrove blue carbon in the Asia-Pacific was in 2017, and since then there has been a steady increase with 2021 having the highest number of peer-reviewed articles (Fig. 4). Multispectral data from Sentinel-2 allowed for precise vegetation classification and quality evaluation, providing a method for identifying areas with abundant biomass (Castillo et al., 2017; Thuy et al., 2020). Sentinel-2 in combination with RapidEye and PlanetScope has been used to study mangrove biomass, with the high-resolution imagery captured by RapidEye (5 m spatial resolution) and PlanetScope (3 m spatial resolution) aiding in better identification of mangroves and allowed better segregation of the canopy and understory (Baloloy et al., 2018).

The Landsat satellites have also been extensively used for estimating mangrove blue carbon in the Asia-Pacific. NASA-USGS's Landsat 8 OLI sensor (launched in 2013) with its open data policy has allowed for frequent observations of mangrove ecosystems with 16 days revisit time and 9 spectral bands recording imagery at a moderate spatial resolution (30 m). It is the second most used multispectral sensor after Sentinel-2 MSI (Fig. 4). Landsat 8 OLI was first used for blue carbon estimation in 2015, with the largest number of articles published in 2021 (Fig. 4). Landsat 8 OLI has facilitated the assessment of temporal dynamics in mangrove blue carbon across decades through the archiving of collected imagery (Sulistiyono et al., 2020). It has also been used in combination with LiDAR data for estimating mangrove height, living biomass, and C

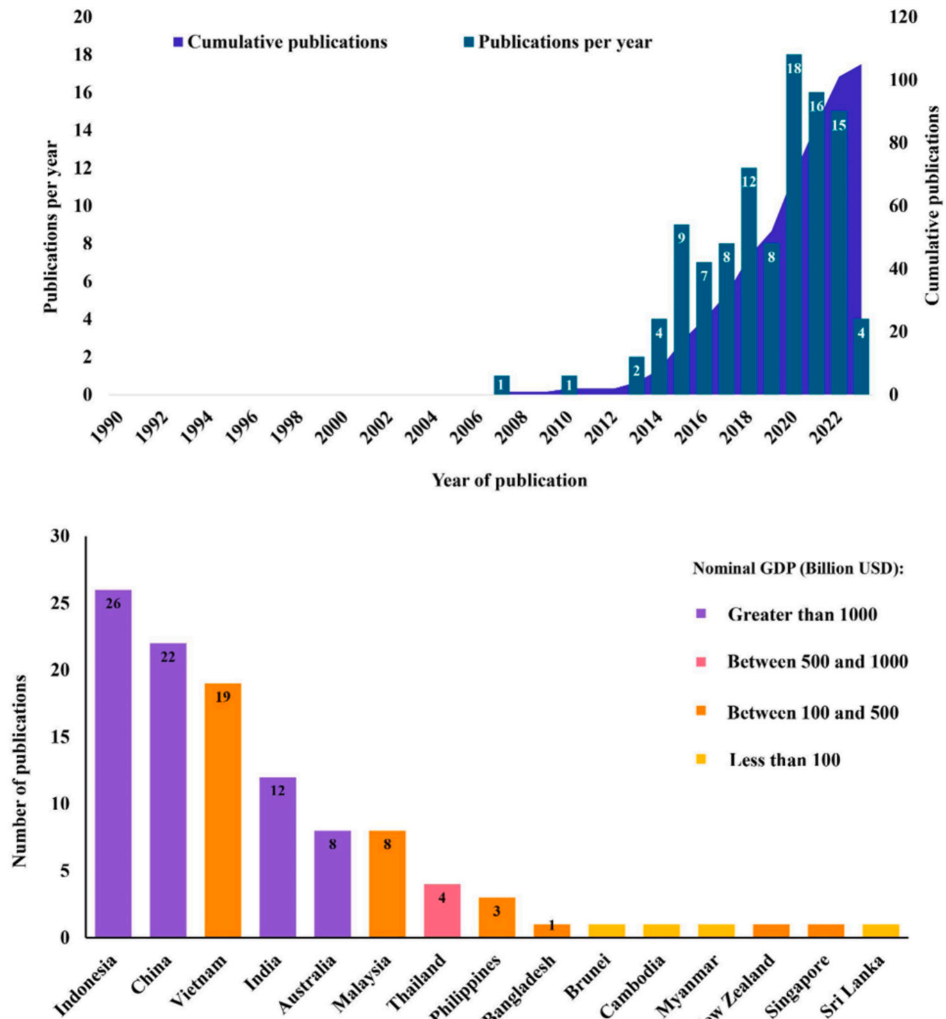


Fig. 3. Number (cumulative and yearly; top) and country-wise (bottom) remote sensing based peer-reviewed articles published on mangrove blue carbon measurements in the Asia-Pacific region from January 1990–June 2023. Countries have been grouped into color codes based on their nominal GDP. The bar for 2023 only includes the first six-months of the year.

stock (Hickey et al., 2018).

The Landsat 5 TM sensor (launched in 1982) provides useful data with its 7 spectral bands ranging from visible to thermal infrared wavelengths (30 m spatial resolution; 16-day revisit time). Its data was first used in 2007 for estimating mangrove blue carbon in the region (Fig. 4). Despite being decommissioned and superseded by newer Landsat missions, Landsat 5 TM has provided a unique opportunity to analyze long-term changes in mangrove biomass and their response to environmental conditions.

Landsat 7 ETM+ (30 m spatial resolution) has also played an important role in mapping and monitoring mangrove biomass since 1999. The capacity of Landsat 7 ETM+ to gather both optical and thermal data improves our understanding of mangrove dynamics, allowing estimation of biomass and its response to changing climate. For estimating mangrove blue carbon in the Asia-Pacific, this satellite was first used in 2016, with the highest number of publications in 2020 (Fig. 4).

Other multispectral satellite data includes QuickBird (2.5 m spatial resolution) which has been successfully used for species identification (Hirata et al., 2014). Mangrove AGC and BGC were also estimated using ALOS AVNIR-2 data (Wicaksono et al., 2016). The use of high spatial resolution imagery such as WorldView-2, Pléiades, and SPOT 5 enabled the accurate estimation of biomass and carbon in heterogeneous landscapes (Wicaksono et al., 2016; Wang et al., 2018a; Muhd-Ekhzarizal et al., 2018; Pham et al., 2020a; Zhu et al., 2020a).

Among the synthetic-aperture radar (SAR) sensors used to study mangrove blue carbon, ALOS-2 PALSAR-2 was the most common, which showed a significant increase after its first use in 2017 (Fig. 4). Launched in 2014 by the Japan Aerospace Exploration Agency (JAXA), this sensor provides day-and-night observation capabilities regardless of the weather or cloud cover. With the capability of canopy penetration, SAR backscatter data can be used to characterize the vegetation structure and predict AGB even in dense tropical mangrove forests (Wicaksono et al., 2016; Pham et al., 2017; Pham et al., 2018; Darmawan et al., 2019; Lucas et al., 2020; Nesha et al., 2020; Pham et al., 2020a). Integration of L-band SAR with a DEM can account for the changes in topography, which could, in turn, be used to refine the estimates of tree height and improve the accuracy of biomass estimation (Vu et al., 2014; Hamdan et al., 2014). The integration of ALOS-2 PALSAR-2 data with multispectral imagery from Sentinel-2 has been found to significantly improve model performance for estimating mangrove AGB (Pham et al., 2020a). Sentinel-1 from ESA (launched in 2014) is also an important tool for assessing mangrove biomass. This satellite has a C-band SAR sensor which has increasingly been used to estimate mangrove blue carbon since its first use in 2017 (Fig. 4). The Airborne SAR (AIRSAR) sensor was used to identify mangrove species from Australia where backscatter values were found to be higher for *Avicennia marina* and *Sonneratia alba* than that of *Rhizophora stylosa* (Mitchell et al., 2005).

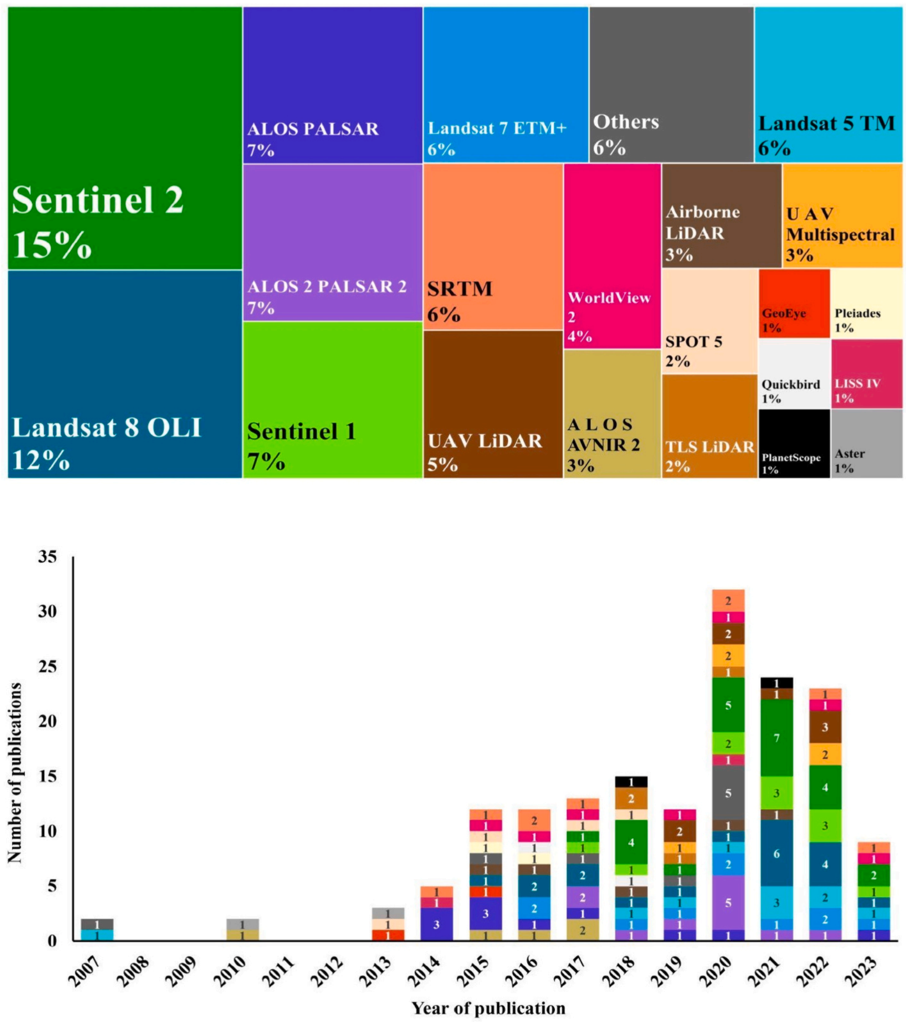


Fig. 4. Percentage of sensors used to measure mangrove blue carbon in the Asia-Pacific region from January 1990–June 2023 (top), and within each year (2007–2023) (bottom). Shades of purple, blue, green, and brown represent L-band ALOS PALSAR sensors, Landsat sensors, Sentinel sensors, and LiDAR-based sensors, respectively. The bar for 2023 only includes the first six months of the year.

Radarsat images were also used for estimating mangrove biomass with regression models (Li et al., 2007). Dual polarization Polarimetric SAR (PolSAR) and Polarimetric Interferometry SAR (PolInSAR) methods were also used to study mangrove blue carbon (Jaya et al., 2017). The radar-based sensor TanDEM-X gathers interferometric data by using two radar satellites that fly in close formation, which makes it easier to create extremely precise DEMs, and has helped in distinguishing between ground and vegetation layers in mangrove forests (Lucas et al., 2020).

Airborne LiDAR to study mangrove blue carbon in the Asia-Pacific was first used in Central Sumatra, providing reliable data for estimating AGB with linear regression models using the canopy height, canopy cover, and the quadratic mean canopy height (Thapa et al., 2015). Airborne LiDAR was also used to study the effect of vegetation structure and species composition on soil carbon storage (Owers et al., 2016).

UAV-based sensors have been recently used to study mangrove blue carbon in the Asia-Pacific region. UAV-LiDAR data provides extensive information about the canopy structure in relatively smaller areas with complex topography (Wang et al., 2019; Li et al., 2019; Nesha et al., 2020; Hu et al., 2020; Wang et al., 2020). Drones such as the DJI Matrice 600 Pro (M600) and DJI Phantom 4 have been used in studies from China and Indonesia (Tian et al., 2022; Wirasatriya et al., 2022). The M600 is a professional-grade drone that has been coupled with the HS40P sensor which can collect LiDAR data, while the Phantom 4 is a rotary-wing UAV that generally carries sensors capable of collecting visual imagery. The EO-1 Hyperion hyperspectral sensor also showed promising results for species classification and mangrove carbon stock estimation in India (Anand et al., 2020). Terrestrial Laser Scanning (TLS) LiDAR data has proved to be an effective method for developing nondestructive allometric models to estimate mangrove blue carbon (Owers et al., 2018; Intarat and Vaiphasa, 2020).

6. Modeling methods used in measuring mangrove blue carbon

Modeling plays a crucial role in accurately quantifying mangrove blue carbon, and the choice depends on the specific research objectives. The use of a genetic algorithm for optimizing radar backscatter parameters in mangrove forests dates back to a 2007 study from China (Li et al., 2007). During the last eight years, there has been a marked transition from parametric modeling (least square linear and non-linear regression) to the use of non-parametric machine learning models (Support Vector Regression (SVR), Random Forest Regression (RFR) or Extreme Gradient Boost Regression (XGBoost or XGBR)) (Fig. 5). In contrast to parametric methods, non-parametric models do not impose rigid assumptions around the functional form or underlying data distribution and are generally seen to perform better (Luong et al., 2018; Meng et al., 2022). This increased flexibility often aids in capturing

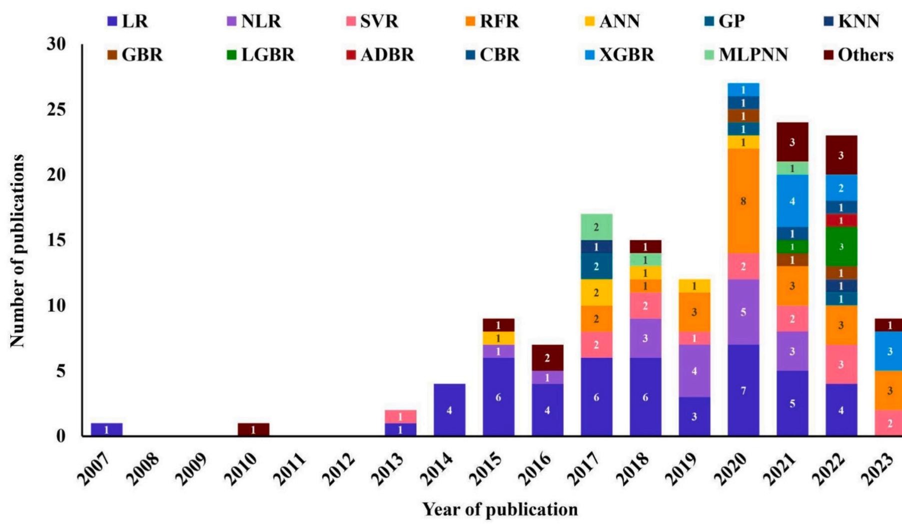


Fig. 5. Modeling approaches used by year for measuring mangrove blue carbon in the Asia-Pacific region during 1990–2023. LR: Linear regression, NLR: Nonlinear regression, SVR: Support Vector Regression, RFR: Random Forest Regression, ANN: Artificial Neural Network, GP: Gaussian Process, GBR: Gradient Boost Regression, LGBR: Light Gradient Boost Regression, KNN: K-nearest neighbor, ADBR: AdaBoost Regression, CBR: CatBoost Regression, XGBR: XGBoost Regression, MLPNN: Multilayer Perceptron Neural Network, Others: GEOBIA, InVEST, GIS-based models etc. The bar for 2023 only includes the first six months of the year.

greater complexity and improves the accuracy of blue carbon quantification.

6.1. Parametric regression models

Early studies have mostly used least square linear regression (LR) models using either multispectral band values, vegetation indices, or SAR backscatter values for estimating mangrove AGB or above-ground carbon (AGC) (Li et al., 2007; Hamdan et al., 2013; Hamdan et al., 2014). Models based on the Normalized Difference Vegetation Index (NDVI) often have significant uncertainty in blue carbon estimations as the multispectral imagery derived-NDVI underestimates the biomass of woody mangrove forests, and SAR data is more accurate (Li et al., 2007). However, extraction of NDVI, and other vegetation indices, from multispectral sensors such as Landsat 5 TM and SPOT-5, have been reported to have good accuracy (Hamdan et al., 2013). An optimized soil-adjusted vegetation index (OSAVI) was found to perform better than NDVI in *Avicennia marina* plantations in the Indian Sundarbans (Manna et al., 2014). The Mangrove Index (MI), which is a vegetation index combining NIR (near infrared) and SWIR (shortwave infrared) bands (i.e., Bands 5 and 6 of Landsat 8 OLI) has been effective in estimating mangrove carbon stocks (Winarso and Purwanto, 2014; Mukhtar et al., 2021).

Among the SAR-based studies, parametric regression models using backscatter from Horizontal-Vertical (HV) polarization have been effective in estimating the total AGB (Hamdan et al., 2014; Pham and Yoshino, 2017). Horizontal-Horizontal (HH) polarization is also effective for some non-dominant species (Pham and Yoshino, 2017). Long-wavelength PolSAR data, such as the L and the P bands, are well correlated with mangrove forest structures (Pham et al., 2020a). AGB parametric regression models based on vegetation indices derived from Sentinel-2 data were more highly correlated to field data than indices extracted from the Landsat 8 OLI sensor (Nguyen and Nguyen, 2021).

The use of species-specific localized allometric models that account for wood density, instead of generic pan-tropical models, showed increased accuracy in model estimates using airborne LiDAR in Australia (Salum et al., 2021). However, generic models were seen to perform better using WorldView-2 imagery in Indonesia (Kamal et al., 2022).

6.2. Machine learning (ML) algorithms

Commonly used machine learning models in association with remote sensing data include Support Vector Machine (SVM), Random Forest (RF), Gradient Boosting Machines (GBMs), and Artificial Neural Network (ANN). The first use of machine learning in the Asia-Pacific using Support Vector Regression (SVR) for mangrove blue carbon was reported from a *Rhizophora-dominated* riverine mangrove forest in southern Thailand, where the model showed relatively good accuracy ($R^2 = 0.66$) (Jachowski et al., 2013). Since then, a large number of studies have used machine learning models. Many machine learning studies have used Python modules such as the Scikit-learn library for model development (Pham et al., 2020a; Pham et al., 2020b; Le et al., 2021; Rijal et al., 2023).

SVM has been found to be robust for handling high-dimensional data and generalizing (Vapnik, 1999; Hastie et al., 2009) and is widely used for hyperspectral image processing (Licciardi et al., 2009; Monnet et al., 2011) and forest AGB estimations. The SVM classification algorithm demonstrated a high accuracy (99 %) in discriminating mangroves from other land cover types in the Philippines (Pillodar et al., 2023). The SVM regression model performed better than RF and MLR for estimating mangrove carbon stocks in Hainan Island, China (Meng et al., 2022). It also outperformed other ML regression models when mangrove plantation AGB was estimated in northern Vietnam using ALOS-2 PALSAR-2 and Sentinel-2 data (Pham et al., 2018).

The RF algorithm is based on a decision tree approach in the ensemble learning family, where a bootstrap sample of the training data is chosen to build uncorrelated decision trees to predict the dependent variable (Breiman, 2001). The final output is a weighted average of all the predictions given by individual decision trees. The performance of the RF algorithm is influenced by hyperparameter tuning and the selection of variables (Tyralis and Papacharalampous, 2017). RF classification models based on a combination of the Inverted Red-Edge Chlorophyll Index (IRECI) and Total Ratio Vegetation Index (TRVI) (red edge and NIR bands of Sentinel-2) have shown good accuracy (kappa coefficient of 0.96) for the classification of mangrove/non-mangrove forests (Suardana et al., 2023). Models based on RFR have performed moderately well (Table 2) in estimating mangrove blue carbon irrespective of the sensor (Wang et al., 2019; Pham et al., 2020a; Sejati et al., 2020; Ghosh et al., 2021; Prakash et al., 2022).

Gradient boosting machines, that include XGBoost (XGB), CatBoost

Table 2
Model accuracy of some selected studies estimating mangrove biomass/carbon, evaluated using the coefficient of determination (R^2) and Root Mean Square Error (RMSE in the units of Mg ha^{-1}).

	Model performance	CBR	ER	GAM	GBR	GLCM	GPR	LGBR	LR	MLPNN	PR	RFR	SVR	XGBR	XGBR-GA	Reference
ALOS-2 PALSAR-2 and Sentinel-2	R^2				0.99		0.51					0.72	0.60; 0.48	0.99		Pham et al., 2018;
	RMSE				39.54		50.23					48.44	0.19; 48.49	28.13		Pham et al., 2020a
ALOS PALSAR and Sentinel-2	R^2	0.59		0.63	0.60; 0.93							0.53; 0.87	0.49	0.68		Pham et al., 2020b;
	RMSE	28.62		66.95	28.30; 28.35							30.58; 39.95	31.86	25.08		Prakash et al., 2022
ALOS -2 PALSAR-2	R^2		0.69				0.48		0.74	0.61	0.76	0.36	0.40			Pham et al., 2017; Luong et al., 2018
	RMSE		28.73				0.38		28.16	0.38	28.03	0.27	0.36			
Pléiades	R^2					0.93			0.63							Wang et al., 2018a
	RMSE					3.76			9.14							
UAV LiDAR	R^2	0.76						0.35				0.62		0.68		Wang et al., 2019; Tian et al., 2022
	RMSE	11.17						18.55				50.36		13.10		
UAV-LiDAR, Sentinel-2	R^2											0.62				Wang et al., 2020
	RMSE											51.03				
Sentinel-1 and Sentinel-2	R^2								0.82–0.84			0.80	0.74	0.89	0.86	Castillo et al., 2017;
	RMSE								27.75–55.81			18.11	38.74	16.45	15.40	Samsu Rijal et al., 2023

Note: CBR: CatBoost Regression, ER: Exponential Regression, GAM: Generalized Additive Model, GBR: Gradient Boost Regression, GLCM: Gray Level Co-occurrence Matrix, GPR: Gaussian Process Regression, LGBR: Light Gradient Boost Regression, LR: Linear Regression, MLPNN: Multilayer Perceptron Neural Network, PR: Polynomial Regression, RFR: Random Forest Regression, SVR: Support Vector Regression, XGBR: XGBoost Regression, XGBR-GA: XGBoost Regression with Genetic Algorithm.

(CB), and Light Gradient Boost (LGB) work by iteratively adding new trees to a model, with each new tree aiming to correct the errors made by the previous ones (Bentéjac et al., 2020). The XGB regression model (XGBR) with Genetic Algorithm (GA) optimization (XGBR-GA) using Sentinel-2, Sentinel-1, and ALOS-2 PALSAR-2 data demonstrated superior performance compared to other machine learning algorithms, making it a promising approach for accurately estimating mangrove AGB (Pham et al., 2020a; Rijal et al., 2023). The XGBR model performed well in a study to estimate AGC using Sentinel-2 and ALOS-2 PALSAR-2 in Indonesia (Rijal et al., 2023). CatBoost effectively processes categorical features directly within the training process, avoiding the need for preprocessing. The CB regression model (CBR) had the highest accuracy among all machine learning models in the estimation of the exotic mangrove *Sonneratia apetala* in China using UAV-LiDAR data (Tian et al., 2022; Table 2).

Optimization algorithms such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) have been used in machine learning models to improve model accuracy (Holland, 1992; Kennedy and Eberhart, 1995). GA aims to mimic natural selection and genetics and makes random changes to the model parameters to find a solution. PSO adjusts the positions of individual data points based on their own best previous positions and the best position found by the whole group, aiding in finding an optimal solution for the model. In North Vietnam, the CBR model coupled with GA optimization (CBR-GA) using Sentinel-2 data performed better than RFR, XGBR, and SVR (Pham et al., 2020c). The CBR model with PSO algorithm for feature selection has been proven to be very effective in mangrove soil organic carbon estimation (Le et al., 2021). The LGB algorithm has shown good performance for high-dimensional data (Li et al., 2018). A study in the mangroves of *Sonneratia apetala, Aegiceras corniculata* and *Kandelia candel* in China using C-band SAR Sentinel-1 and multispectral images of Sentinel-2 showed LGB with PSO feature selection outperformed all other ML models (Huang et al., 2022).

ANN regression employs gradient-based learning to establish a neural network for capturing complex connections between inputs and outputs through feed-forward architectures (Yuan et al., 2017). In a study at the Can Gio Biosphere Reserve in Vietnam, ANN achieved higher prediction accuracy than SVR and Gaussian Process (GP) regression (Do et al., 2022). The multilayer perceptron neural network (MLPNN) model, a neural network-based model, has been seen to outperform other machine learning techniques in mangrove AGB estimation in Vietnam using ALOS-2 and PALSAR-2 backscatter coefficients (Pham et al., 2017).

6.3. *Other geospatial models*

Geographic object-based image analysis (GEOBIA) is commonly used in land-use/land-cover mapping, for example; where the entire image is classified spectrally into information classes such as vegetation (Radoux and Bogaert, 2017). The GEOBIA model has successfully classified mangrove species and estimated mangrove AGC stocks using high-resolution remote sensing imagery from WorldView-2 by incorporating species-specific allometric equations, with a good level of accuracy (84 %) for species classification (Hidayatullah et al., 2023).

The Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model is designed to assess and quantify the ecosystem services offered by various landscapes/seascapes. The Carbon module within InVEST enables the assessment of carbon emissions resulting from land use change and has been used in combination with multi-temporal Landsat data to investigate the temporal dynamics of mangrove blue carbon (Islam et al., 2022; Jia et al., 2022; Kadaverugu et al., 2022).

7. An overview of different attributes measured by remote sensing

A variety of attributes of mangrove blue carbon have been determined based on remote sensing and modeling (Fig. 6). Among the reviewed articles, the main blue carbon attribute estimated was AGC (based on remotely sensed measures including tree height, forest area, canopy cover, etc. and predicted based on location/species-specific models) while BGC (biomass and soil/sediment) was less studied. Similarly, the studies based on the valuation of mangrove carbon stocks followed by rehabilitation initiatives were limited. This highlights the importance of expanding research toward various blue carbon attributes that have not yet been extensively explored.

7.1. Mangrove quality

Near-real time monitoring of mangroves is critical in understanding their behavior, adaptability, and response to natural/anthropogenic stressors. Since the early 2000s, there have been remote sensing-based studies on mangrove productivity dynamics. Gross Primary Productivity (GPP) is an important indicator of the overall productivity and vitality of an ecosystem. The quality of mangrove vegetation in Indian Sundarbans was determined based on GPP integrating field-based estimations of GPP (Leaf Area Index (LAI) and chlorophyll content) and Landsat 8 OLI data (Kumar and Kumar Das, 2023). This has led to a more comprehensive and reliable assessment of GPP. In addition, Landsat 5 TM and SPOT 5 using NDVI, OSAVI, and SAVI (soil-adjusted vegetation index) were useful for evaluating the carbon stock and quantifying changes that occurred due to deforestation, wood extraction, and forest degradation over the years (Hamdan et al., 2013).

7.2. Impact of disturbance on mangrove blue carbon measured by remote sensing

Mangroves face several threats due to climate change impacts, including rising sea levels, and temperatures, and changes in the frequency and severity of precipitation and storm patterns. Among all these factors, sea level rise has been identified as the greatest threat (Jachowski et al., 2013; Pham et al., 2018). A remote sensing-based study (airborne LiDAR, RGB, and hyperspectral imagery) from Australia was successful in assessing the impact of hypersalinity on the mangrove dieback (Dittmann et al., 2022). Anthropogenic disturbances including deforestation (due to unlawful logging, urbanization, palm/coconut cultivations, and aquaculture) have led to a degradation of mangrove ecosystems in the Asia-Pacific (Kadaverugu et al., 2022; Worthington et al., 2020; Wirasatriya et al., 2022; Bournazel et al., 2015; Aslan et al., 2016; Wang et al., 2018b; Zhu et al., 2020a; Eddy et al., 2021; Nguyen et al., 2021).

A study from Indonesia (Belitung Island) revealed the impact of land conversion and mining on the degradation of mangrove blue carbon stock (Hermon et al., 2018). Similarly, an expansion of coconut plantations has led to a significant destruction of mangrove forests in South Sumatra (Eddy et al., 2021). Aquaculture has historically replaced Indonesian mangroves, and Semarang's urban growth caused a 20,500-ton loss in just 4 years (Eddy et al., 2021). Vietnam's Can Gio biosphere reserve saw a change of around 9.5 % in 20 years, with the biomass decreasing in the core zone (Sejati et al., 2020). Industrial development over the years in the coastal area of Metropolitan Semarang, Indonesia has led to habitat fragmentation and degradation, reducing mangrove cover and carbon sequestration potential (Sejati et al., 2020). Similarly, in Indonesia (South Sumatra) extensive shrimp farming has altered the landscape, resulting in habitat fragmentation and disruption of migratory pathways for various species (Eddy et al., 2021).

In the Indian Sundarbans, 107 km^2 of mangrove area was lost in four decades (1975 to 2013) to various anthropogenic activities, emitting 1567.98 ± 551.69 Gg, with a rate of emission at 41.26 ± 14.52 Gg per year (Akhand et al., 2017). The Puttalam lagoon in Sri Lanka witnessed losses of 191,584 Mg C due to the implementation of shrimp aquaculture in the mangrove forest area, an activity which was expanded by 2777 % within three decades (Bournazel et al., 2015). In China, aquaculture expansion has resulted in mangrove degradation and subsequent carbon stock decline, highlighting the importance of implementing sustainable coastal development (Xu et al., 2023).

8. Variations of mangrove blue carbon sequestration capacity captured by remote sensing

Mangrove carbon stocks have been recognized within global initiatives, such as the REDD+ (Reducing Emissions from Deforestation and Forest Degradation) framework due to their importance in national and global carbon accounting.

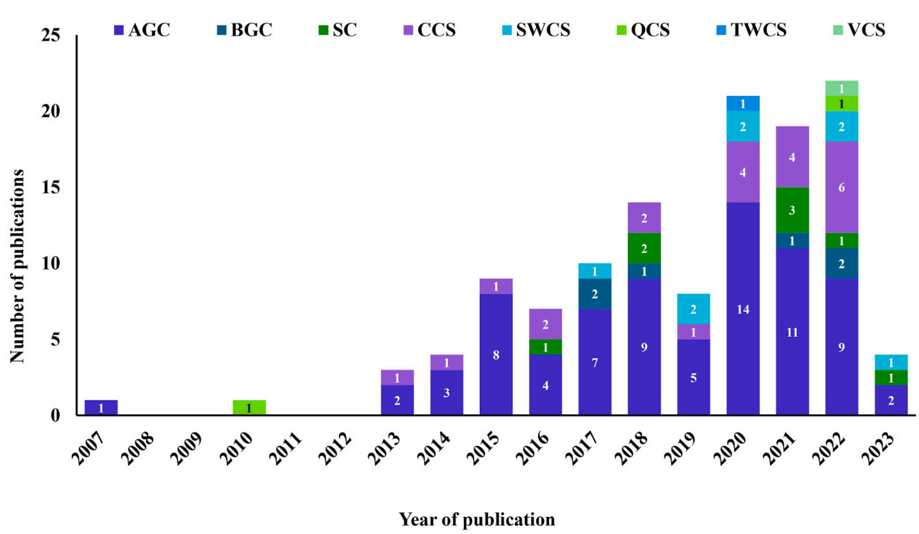


Fig. 6. Types of mangrove blue carbon attributes estimated using remote sensing in the Asia-Pacific over time since 2007 (AGC: Above Ground Carbon; BGC: Below Ground Biomass Carbon; SC: Soil Carbon; CCS: Change in Carbon Stock; SWCS: Species Wise Carbon Stock; QCS: Quality of Carbon Stock; TWCS: Typology Wise Carbon Stock; VCS: Valuation of Carbon Stock). The bar for 2023 only includes the first six months of the year.

8.1. Environmental factors

The carbon sequestration capacity of mangroves in the Asia-Pacific area is inextricably tied to their geomorphology (shoreline configuration, elevation, and sediment dynamics), hydrology, and climate (Thom, 1984; Duke et al., 1998; Twilley et al., 1998; Balke and Fries, 2016). Tidal patterns, salinity, and freshwater influx all impact mangroves, ultimately influencing their carbon sequestration capacity. Analysis from high-resolution UAV imagery has shown that the community of similar tree species still exhibits variations in tidal level, salinity, and planting patterns (Bin et al., 2022). The photochemical reflectance index (PRI) has been used to demonstrate that significant temporal variations in environmental factors (photosynthetically active radiation (PAR), air temperature, and vapor pressure deficit (VPD)) directly influence photosynthetic activity, which in turn impacts mangrove blue carbon dynamics (Zhu et al., 2019).

8.2. Location

The intricate relationship between mangrove forests and their environment is reflected by the wide variation in blue carbon observed across diverse geographical locations within the Asia-Pacific region (Table 3). On average, the aboveground and belowground biomass components contain approximately 50 % and 39 % carbon, respectively (Kauffman and Donato, 2012). Based on our review, the highest AGB was recorded from Indonesia (328 Mg ha^{-1}), followed by Australia (230.6 Mg ha^{-1}) and Vietnam (230.14 Mg ha^{-1}) (Table 3). The BGB (reported only in a few studies) was highest in Thailand (95 Mg ha^{-1}), followed by Australia (20 Mg ha^{-1}), and Indonesia (8.60 Mg ha^{-1}) (Table 3).

8.3. Mangrove species

Southeast Asia boasts the highest mangrove diversity globally. Among the screened articles explicitly mentioning mangrove species, *Avicennia marina* emerges as the most widely studied using remote sensing within the Asia-Pacific. Other extensively examined species using remote sensing include *Rhizophora apiculata*, *Rhizophora mucronata*, *Sonneratia alba*, *Ceriops tagal*, *Aegiceras corniculatum*, and *Heritiera fomes*.

In Indonesian Papua, data from ALOS PALSAR and SRTM DEM showed a distinct contrast in mean standing biomass between short canopy stands dominated by *Avicennia* and *Sonneratia* and mature tall canopy stands of *Rhizophora* (Aslan et al., 2016). In East Java, *Rhizophora apiculata* had a higher mean AGC than *Ceriops tagal*, *Sonneratia alba*, and *Bruguiera gymnorrhiza* (Hidayatullah et al., 2023). LiDAR metrics have been used to determine canopy heights (converted to AGB using regression models) of mangrove forests of *Rhizophora stylosa*, *Ceriops tagal*, and *Sonneratia alba* in northern Australia and New Zealand (Salum et al., 2021; Suyadi et al., 2020). The comparisons (Table 4) may have been influenced by other factors including stand characteristics, remote sensing method, and modeling approaches.

8.4. Carbon sequestration of planted mangroves and variation based on age

Restoration and plantation of mangroves necessitate meticulous site monitoring. China's largest artificially planted mangroves of *Sonneratia apetala* mapped using GaoFen-2 and GaoFen-3 sensors had an average estimated AGB of 137.89 Mg ha^{-1} (Zhu et al., 2020b). Similarly, planted mangroves of *Avicennia marina* in the Henry Island of the Indian Sundarbans studied using ISRO's ResourceSat-2 LISS IV sensors developed 6.64 Mg C ha^{-1} (upper range) within just five years of plantation establishment (Manna et al., 2014). The mapping of AGB (using ALOS-2 PALSAR-2) in degraded mangroves restored using *Avicennia alba* and *Rhizophora* spp. in East Kalimantan, Indonesia had an average AGB of 181 Mg ha^{-1} (Nesha et al., 2020).

The carbon sequestration capacity of mangrove forests varies with the age of the mangroves, with old, contiguous mangrove patches containing a higher density of biomass carbon than fragmented, river-fringing, or restored mangroves (Friess et al., 2016). Natural mangrove stands may possess an AGC storage capacity of up to 250 Mg C ha^{-1}, a level of carbon sequestration that remains unparalleled by planted counterparts (Hamdan et al., 2013). Another study in the Richmond River estuary in Australia using data collected from a UAV exhibited a difference in AGB of up to 80 Mg ha^{-1} between natural and

Table 3
Variation in pools of biomass and blue carbon stocks in countries of the Asia-Pacific region as measured by remote sensing (in studies published from January 1990–June 2023). Biomass and blue carbon stocks are expressed as a min-max range and/or (mean) or (mean ± standard deviation) in brackets. AGB/BGB (Mg ha^{-1}); AGC/BGC/Soil C (Mg C ha^{-1}).

Country	Region	AGB	BGB	AGC	BGC	Soil C	Reference
Australia	East coast	–	–	–	–	74.5–88.5	Owers et al., 2016
	North-Western (semi-arid)	(70)	(20)	–	–	–	Hickey et al., 2018
	South	–	–	(48)	–	(101.72 ± 15.97)	Dittmann et al., 2022
	Southeastern	152.1–230.6					Navarro et al., 2020
Bangladesh		(154.17 ± 12.84)	–	–	–	–	Hu et al., 2020
China	Hainan Island		–	(44.7 ± 21.1)	–	–	Meng et al., 2022
	Kangxiling area	38.23–171.80 (94.37)					Tian et al., 2022
	Southeast (sub tropical)			1–153			Wang et al., 2018b
India			–	104.72–306.70		–	Anand et al., 2020
	Maharashtra			(21.7)	(18.1)		Patil et al., 2015
	Kachchh, Gujarat	0.1–213					Vaghela et al., 2021
Indonesia		8–328 (38.60 ± 20.79)	(8.60 ± 4.24)	2.52–123.89 (57.16)	–	–	Hastuti et al., 2018; Wirasatriya et al., 2022; Rijal et al., 2023
New Zealand	Auckland Region	–	–	(40.2)	–	–	Suyadi et al., 2020
Papua New Guinea		(148.94 ± 46.75)	–	–	–	–	Hu et al., 2020
Philippines	Palawan	1.1–210 (65.1)	–	–	–	–	Castillo et al., 2017
Sri Lanka	Puttalam lagoon	–	–	(159)	(199.18 ± 19.02)	–	Bournazel et al., 2015
Thailand	Suksamran subdistrict, Ranong Province	(250)	(95)	(113)	(42)	–	Jachowski et al., 2013
Vietnam	Hai Phong city	36.22–230.14 (87.67)	–	–	–	–	Pham et al., 2018

Table 4
Above-ground biomass and carbon of different mangrove species in Asia-Pacific region as measured by remote sensing and reported in studies published from January 1990–June 2023. Values shown are expressed as a min-max range or and/or (mean) or (mean ± standard deviation).

Species	Country	AGB (Mg ha^{-1})	AGC (Mg C ha^{-1})	References
Aegiceras corniculatum	China	11.3–122.88	–	Huang et al., 2022
	China	(99.24)	–	Bin et al., 2022
	India	–	(149.90 ± 5.57)	Anand et al., 2020
Avicennia marina	China	–	(95.25)	Bin et al., 2022
	China	–	(47.4 ± 6.2)	Li et al., 2019
	New Zealand	–	(46.3 ± 1.5)	Suyadi et al., 2020
	New Zealand	–	(24.9 ± 0.9)	Suyadi et al., 2020
	Indonesia	(19)	–	Mukhtar et al., 2021
Avicennia/ Sonneratia dominated forest	Indonesia	(237.52 ± 98.20)	–	Aslan et al., 2016
Bruguiera dominated forest	Indonesia	(295.09 ± 86.17)	–	Aslan et al., 2016
Bruguiera gymnorrhiza	Indonesia	–	2.19–63.11	Hidayatullah et al., 2023
Cerbera odollam	India	–	(154.78 ± 18.39)	Anand et al., 2020
Cynometra iripa	India	–	(149.90 ± 5.57)	Anand et al., 2020
Ceriops tagal	Indonesia	20.6–96.9	–	Hidayatullah et al., 2023
	Australia	(7.4)	–	Salum et al., 2021
Excoecaria agallocha	India	–	(143.48 ± 17.39)	Anand et al., 2020
Heritiera littoralis	India		(145.55 ± 7.88)	Anand et al., 2020
Heritiera fomes	India		(141.95 ± 10.60)	Anand et al., 2020
Intsia bijuga	India		(137.87 ± 12.57)	Anand et al., 2020
Kandelia candel	China	4.6–43.12		Huang et al., 2022
Kandelia obovata	China		(148.03)	Bin et al., 2022
	China		(94.0 ± 25.3)	Li et al., 2019
	Vietnam		27.6–209	Pham and Yoshino, 2017
Rhizophora mucronata	Indonesia		35.9–80	Hidayatullah et al., 2023
	Indonesia		29.8–175.8	Suardana et al., 2023
Rhizophora apiculata	Indonesia		24.6–167.1	Hidayatullah et al., 2023
	Indonesia	(232.7)		Mukhtar et al., 2021
	Indonesia		31–101	Suardana et al., 2023
Rhizophora stylosa	Australia	(179)		Salum et al., 2021
Rhizophora dominated forest	Indonesia	(353.30 ± 98.43)		Aslan et al., 2016
Sonneratia alba	Indonesia		0.47–101.8	Hidayatullah et al., 2023
	Australia	(252)		Salum et al., 2021
	Indonesia		31.8–145.7	Suardana et al., 2023
Sonneratia apetala	India		(137.83 ± 15.30)	Anand et al., 2020
	China	8.5–207		Huang et al., 2022
	China		(128.6 ± 38.13)	Li et al., 2019
	China	7.31–114.03		Tian et al., 2022
Sonneratia caseolaris	Vietnam	2.8–299		Pham et al., 2017
	Vietnam	2.75–161.5		Pham and Yoshino, 2017
	China		(111.5 ± 31.7)	Li et al., 2019
Xylocarpus granatum	India		(150.50 ± 15.51)	Anand et al., 2020
Xylocarpus mekongensis	India		(130.39 ± 12.70)	Anand et al., 2020

planted mangroves (Navarro et al., 2020), highlighting the importance of the conservation and restoration of natural mangrove forests.

The growth rates of mangrove plantations are often very rapid, particularly during the first few years after establishment. The growth of the Matang mangroves in Malaysia determined using a combination of Landsat, ALOS PALSAR, TanDEM-X, and WorldView-2 images revealed the growth rate to be higher during the first few years (> 20 Mg ha^{-1} yr^{-1}) compared to the growth rate after 13 years (< 5 Mg ha^{-1} yr^{-1}) (Lucas et al., 2020).

9. Research gaps, challenges, opportunities and recommendations

As highlighted by the reviewed articles, knowledge/research gaps exist in remote-sensing based mangrove blue carbon estimations across the Asia-Pacific region, particularly in mangrove ecosystems with complex vegetation structures and topography (Luong et al., 2018; Tian et al., 2022). Despite having high mangrove cover across Bangladesh, Myanmar, and Papua New Guinea, significant research gaps exist around use of remote sensing-based blue carbon estimations (Figs. 1 and 3), that may be attributable to financial constraints.

Given the species complexity in the Asia-Pacific region, further studies should include metrics related to species richness, community completeness, biodiversity, and vegetation structural characteristics when estimating AGB (Pham et al., 2020a; Nguyen and Nguyen and Nguyen, 2021, Wicaksono, 2017). In addition, further research is recommended to quantify differences in species-specific biomass, and other biophysical properties, especially in areas with high mangrove cover densities such as in Indonesia (Wicaksono, 2017; Zablan et al., 2023). Significant knowledge gaps also exist in areas including the evidence-based biogeochemical carbon fluxes (in 55 % of the Asia-Pacific countries), sediment-to-sea carbon exports (only reported from nine countries in the Asia-Pacific region), and carbon export fluxes in Indonesian mangroves (Sharma et al., 2023). In addition, remote sensing based estimations of mangrove litter layers have a high potential for further research.

The accuracy of the biomass estimates depends on the choice of sensor, platform, and modeling method, especially in areas with complex topography/canopy structure (Pham et al., 2018). Fusion of remote sensing data such as high-resolution WorldView-2 imagery and LiDAR (Pham et al., 2020b), field-based data, and best machine learning algorithms can greatly improve estimates of mangrove AGC (Wicaksono et al., 2016; Wicaksono, 2017; Pham et al., 2018; Nguyen and Nguyen and Nguyen, 2021). Integrating Sentinel-2 imagery with well-planned field surveys can provide a means of scaling estimates of mangrove carbon stocks to regional levels (Meng et al., 2022). The limitations associated with sensors should be investigated to improve their performance. One such example is the saturation of backscatter intensity in SAR/ PolSAR, once AGBs exceed a certain value, leading to inaccurate estimations in dense forests (Jaya et al., 2017; Pham and Yoshino, 2017; Darmawan et al., 2019; Tu et al., 2019). The accuracy of AGC estimates could be improved by the appropriate use of multispectral or pan-sharpened imagery to generate vegetation indices such as NDVI, Enhanced Vegetation Index (EVI), and Ratio Vegetation Index (RVI), and integration of terrain variables such as slope and elevation derived from LiDAR data (Pham et al., 2020b).

The recent advances in UAV-based remote sensing should be fully utilized to improve data accuracy in estimating mangrove blue carbon at a higher spatial resolution (Li et al., 2019; Hu et al., 2020). In addition, the flexibility offered by UAVs to control temporal resolution should be used to mitigate the influence of environmental factors (tides and floods) that usually affect the precision of mangrove blue carbon measurements (Li et al., 2019; Hu et al., 2020; Zhu et al., 2020a). The use of UAV-LiDAR with allometric equations has provided accurate and efficient methods to estimate AGB and map invasive species, supporting the conservation of native mangrove ecosystems (Tian et al., 2022).

Uncertainties in model estimations are another limitation that occurs when working with multiple merged data sets, that have mixed pixel issues and different spatial/spectral resolutions (Zhu et al., 2022). The effectiveness and accuracy of models and variables have been shown to vary across different locations and species (Luong et al., 2018). Model accuracies should be improved by employing feature selection methods, such as Recursive Feature Elimination (RFE) and Mutual Information (MI) to identify the most important remote sensing variables in predicting AGB of mangrove forests (Pham et al., 2020b). Once all efforts have been taken to improve data accuracy, it is important to quantify uncertainties associated with the estimation (Hirata et al., 2014).

Advances in computing power have provided several opportunities to use superior machine learning algorithms (Table 2) such as SVR, RF, and GBR to improve the accuracy of estimations (Pham et al., 2020a; Pham et al., 2020b; Prakash et al., 2022; Samsu Rijal et al., 2023). As an example, by integrating field survey data with ALOS-2 PALSAR data, the Multilayer Perceptron Neural Network (MLPNN) model estimated AGB with high accuracy in a tropical mangrove ecosystem (Pham et al., 2017).

Quantification of BGC including carbon stored in soils and dead wood remains a challenge (Vu et al., 2014; (Wicaksono et al., 2016; Hu et al., 2020). The low accuracy of BGC estimates compared to AGC has been recognized as a significant source of error (Patil et al., 2015; Wicaksono et al., 2016; Hu et al., 2020). The BGC estimates are generated through modeled relationships with a set of above-ground biophysical properties (Wicaksono et al., 2016). Therefore, the availability and credibility of ground reference data greatly influence the accuracy of model predictions (Hu et al., 2020). However, some studies fail to conduct a thorough investigation of model accuracies in biomass estimation by gathering ground reference data (Pham et al., 2018). Even when ground reference data is collected, it is often challenging to maintain the quality of the data due to issues such as lack of representativeness, low sample size, issues with validity and reliability of field data, and biases in sampling design (Wang et al., 2018b; Kadaverugu et al., 2022; Suardana et al., 2023). Thus, it is important to explore further techniques for improving the accuracy of estimating different carbon pools (Vu et al., 2014).

Ecological attributes of mangroves that determine the capacity of provisioning (timber and NTFP), and regulating ecosystem services (carbon sequestration and coastal protection) should be researched thoroughly to obtain a better understanding (Suardana et al., 2023). Variation in mangrove biophysical typology across regions and ecosystems is not fully understood and is a function of the climate, hydrology, and anthropogenic impacts (Worthington et al., 2020). Long-term monitoring of localized mangrove carbon sequestration is needed in many places in the Asia-Pacific region that characterize land use change, ecosystem fragmentation, and underlying drivers of change (Jachowski et al., 2013; Sejati et al., 2020; Do et al., 2022).

Development of standardized protocols and coordination between global/regional monitoring programs are needed to assess the spatio-temporal dynamics of mangrove ecosystems (Kadaverugu et al., 2022; Anand et al., 2020). Standardized methodologies help improve data quality and comparability across study regions, which would also help address key challenges associated with collecting accurate information (Anand et al., 2020).

For climate change mitigation/adaptation, data-driven strategies should be implemented to protect and conserve remaining mangrove ecosystems (Wirasatriya et al., 2022; Gugerty and Karlan, 2018). It is recommended that mangrove biomass is monitored every 2–5 years, to track and understand the temporal dynamics of mangrove cover/C stock (Tu et al., 2019; Wong et al., 2020; Mahasani et al., 2021) which is useful in sustainable management of mangroves, and early detection of threats (Wong et al., 2020; Suardana et al., 2023). With the widely expanding voluntary carbon markets, there is a financial incentive for countries to improve the credibility of their data (Pham et al., 2020c).

Overall, remote sensing-based measurement significantly enhances monitoring and reporting systems while providing invaluable guidance for sustainable and adaptive management strategies. This approach could form the basis for crucial policy recommendations, particularly at a large scale, contributing to impactful policymaking (Sakti et al., 2020).

For sustainable management, it is imperative to implement and prioritize country-specific policies that address various key areas, encompassing i). Protected areas and reserves with varying levels of protection (strict no-take zones to sustainable use zones); ii). Legislation and regulation (to protect mangroves from deforestation, and unsustainable exploitation); iii). Integrated Coastal Zone Management (policies involving stakeholder engagement, participatory decision-making, and the integration of environmental, social, and economic considerations into coastal planning/management); and iv) International agreements and initiatives (such as Ramsar Convention on Wetlands, the Convention on Biological Diversity (CBD), and the United Nations Framework Convention on Climate Change (UNFCCC)).

The development of standardized protocols and coordination between global/regional monitoring programs would allow policymakers/decision-makers to work together in creating cohesive management strategies/policies to minimize threats at a regional level (Kadaverugu et al., 2022). Policy instruments such as Payments for Ecosystem Services (PES) exist in this region where mangrove forests generate benefits for forest conservation by assessing the value gained from preventing forest loss/degradation (Thuy et al., 2023).

10. Conclusions

The use of remote sensing data from a variety of sources in combination with advanced modeling approaches has greatly contributed to an improved understanding of spatiotemporal dynamics of mangrove blue carbon in the Asia-Pacific region. Despite these advances, few remote sensing studies on mangrove blue carbon were identified in countries such as Myanmar, Bangladesh, and Papua New Guinea despite their high mangrove extent. During 1990–2023, openly available data from multispectral sensors was widely used for studying mangrove blue carbon. The most preferred sensor was Sentinel-2 MSI, accounting for 14.5 % of overall usage, followed by Landsat 8 OLI (11.5 %), ALOS 2 PALSAR 2 (7.3 %), ALOS PALSAR (7.2 %), Sentinel-1 (6.7 %), Landsat 7 ETM+ (6.1 %), Landsat 5 TM (5.5 %), SRTM DEM (5.5 %), and UAV-LiDAR (4.5 %). The use of UAV-based sensors has increased considerably over recent years. Over time, parametric modeling approaches (linear/non-linear regression) have transitioned into non-parametric ensemble machine learning models (SVM, RF, and XGBoost), significantly improving the accuracy of estimating mangrove blue carbon. The carbon sequestration of mangroves was found to vary based on location, species, plantation type, and age.

Our review confirms the existence of knowledge gaps and the need for further research on mangrove blue carbon assessment and ways to increase the accuracy and precision, and detailed assessment of biogeochemical carbon fluxes/BGC. In addition, valuation followed by rehabilitation initiatives (beneficial in the voluntary carbon market) were less studied.

To improve the accuracy of estimating mangrove blue carbon, it is vital to adopt standardized/coordinated and innovative methodologies accompanied by credible information and actionable data (i.e., selection of the most suitable technical methodology, remote sensing approach, choice of allometric models, and machine learning algorithms). Accurate and precise data on mangrove blue carbon would provide multiple benefits including opportunities for a voluntary carbon market, which would benefit the environment and local communities in the Asia-Pacific region.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

CRediT authorship contribution statement

Abhilash Dutta Roy: Data curation, Formal analysis, Investigation, Methodology, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Pavithra S. Pitumpe Arachchige:** Data curation, Formal analysis, Investigation, Methodology, Project administration, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Michael S. Watt:** Investigation, Methodology, Supervision, Writing – original draft, Writing – review & editing. **Apoorwa Kale:** Methodology, Writing – original draft, Writing – review & editing. **Mollie Davies:** Methodology, Writing – original draft, Writing – review & editing. **Joe Eu Heng:** Methodology, Writing – original draft, Writing – review & editing. **Redeat Daneil:** Methodology, Writing – original draft, Writing – review & editing. **G.A. Pabodha Galgamuwa:** Methodology, Writing – original draft, Writing – review & editing. **Lara G. Moussa:** Methodology, Visualization, Writing – review & editing. **Kausila Timsina:** Methodology, Supervision, Writing – original draft. **Ewane Basil Ewane:** Investigation, Methodology, Supervision, Writing – original draft, Writing – review & editing. **Kerrylee Rogers:** Writing – review & editing. **Ian Hendy:** Writing – original draft, Writing – review & editing. **Andrew Edwards-Jones:** Writing – review & editing. **Sergio de-Miguel:** Writing – review & editing. **John A. Burt:** Writing – review & editing. **Tarig Ali:** Writing – review & editing. **Frida Sidik:** Resources, Writing – review & editing. **Meshal Abdullah:** Writing – review & editing. **P. Pandi Selvam:** Writing – review & editing. **Wan Shafrina Wan Mohd Jaafar:** Writing – review & editing. **Isuru Alawatte:** Writing – review & editing. **Willie Doaemo:** Writing – review & editing. **Adrián Cardil:** Writing – review & editing. **Midhun Mohan:** Conceptualization, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgment

We would like to thank the following individuals for their support during the manuscript writing/review process: Daniel A. Friess, Akshay Sharma, Luisa Fernanda Velasquez Camacho, Jorge Montenegro, Emma Sullivan, and Marcela Rondon. We are also grateful to the anonymous reviewers whose comments have greatly improved the manuscript.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2024.173270.

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