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Remote sensing for cost-effective blue carbon accounting

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ABSTRACT

Blue carbon ecosystems (BCE) include mangrove forests, tidal marshes, and seagrass meadows, all of which are currently under threat, putting their contribution to mitigating climate change at risk. Although certain challenges and trade-offs exist, remote sensing offers a promising avenue for transparent, replicable, and cost-effective accounting of many BCE at unprecedented temporal and spatial scales. The United Nations Framework Convention on Climate Change (UNFCCC) has issued guidelines for developing blue carbon inventories to incorporate into Nationally Determined Contributions (NDCs). Yet, there is little guidance on remote sensing techniques for monitoring, reporting, and verifying blue carbon assets. This review constructs a unified roadmap for applying remote sensing technologies to develop cost-effective carbon inventories for BCE – from local to global scales. We summarise and discuss (1) current standard guidelines for blue carbon inventories; (2) traditional and cutting-edge remote sensing technologies for mapping blue carbon habitats; (3) methods for translating habitat maps into carbon estimates; and (4) a decision tree to assist users in determining the most suitable approach depending on their areas of interest, budget, and required accuracy of blue carbon assessment. We designed this work to support UNFCCC-approved IPCC guidelines with specific recommendations on remote sensing techniques for GHG inventories. Overall, remote sensing technologies are robust and cost-effective tools for monitoring, reporting, and verifying blue carbon assets and projects. Increased appreciation of these techniques can promote a technological shift towards greater policy and industry uptake, enhancing the scalability of blue carbon as a Natural Climate Solution worldwide.

Abbreviations: COP27, 27th UN Climate Change Conference of the Parties; ATLAS, Advanced Topographic Laser Altimeter System; AI, Artificial intelligence; AUV, Autonomous underwater vehicle; BCE, Blue carbon ecosystems; BGR, Blue-Green-Red; DB, Deadwood biomass; GEDI, Global Ecosystem Dynamics Investigation; GHG, Greenhouse gas; HR, High resolution; HWP, Harvested wood products; IPCC, Intergovernmental Panel on Climate Change; LiDAR, Laser imaging, detection, and ranging; L, Litter; LAGB, Living above-ground biomass; MMU, Minimum mapping unit; MRV, Monitoring, reporting, and verifying; NISAR, NASA-ISRO Synthetic Aperture Radar; NDCs, Nationally Determined Contributions; NCS, Natural climate solutions; NbS, Nature-based Solutions; REDD+, Reducing Emissions from Deforestation and forest Degradation; ROV, Remotely operated vehicle; SWOT, Surface Water and Ocean Topography; SAR, Synthetic Aperture Radar; UNFCCC, United Nations Framework Convention on Climate Change; UAV, Unmanned aerial vehicle; VCS, Verified Carbon Standard; VCU, Verified Carbon Units.

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Remotely operated vehicles (ROV)
Minimum mapping unit (MMU)
Monitoring, reporting, and verifying (MRV)

1. Introduction

There is now a strong consensus that greenhouse gas (GHG) emission reduction alone will be insufficient to achieve the climate target set under the Paris Agreement to hold the rise in global average temperature to <1.5 °C above pre-industrial levels (Livingston and Rummukainen, 2020). Consequently, all climate change mitigation pathways identified by the Intergovernmental Panel on Climate Change (IPCC) require additional solutions to help the world meet net-zero emissions targets, including carbon capture technologies and changes to agriculture, forestry, and other land uses (Rogelj et al., 2018). Natural climate solutions (NCS) are a broad suite of conservation, restoration, and improved land management strategies that enhance carbon storage and/or avoid GHG emissions in landscapes and wetlands, with higher cost-effectiveness than current carbon capture technologies. Examples include avoiding deforestation, reforestation, afforestation, and improved land stewardship, and NCS possess recognised potential for removing up to 23.8 petagrams CO_2-equivalent per year (Pg CO_2-eq y^{-1}) of global emissions (Griscom et al., 2017). However, the cumulative carbon abatement costs of achieving climate targets, estimated at US$ 10–100 trillion, constitute a barrier to uptake (van Vuuren et al., 2020). Cost-effective and reliable technologies to monitor carbon abatement gains are therefore imperative to enhance the use and scalability of NCS.

One NCS that has received substantial attention over the past decade is blue carbon. This refers more specifically to blue carbon ecosystems (BCE), such as mangrove forests, tidal marshes, and seagrass meadows. These habitats can sequester and store large volumes of organic carbon, underscoring their key role in global biogeochemical cycles. Importantly, BCE have GHG removal rates and long-term carbon storage potential far higher than terrestrial forests (Taillardat et al., 2018). The anoxic substrates of BCE can trap carbon for millennia, meaning that maintaining the health of these ecosystems represents an effective climate mitigation policy (Duarte et al., 2013; Lovelock and Duarte, 2019). Globally, soil stocks from BCE are estimated to represent 8–33 billion tonnes of carbon, and average densities of soil carbon stocks are estimated at 386 Mg ha^{-1} for mangrove forests, 255 Mg ha^{-1} for tidal marshes, and 108 Mg ha^{-1} for seagrass meadows (Macreadie et al., 2021). BCE are under threat from anthropogenic pressures, including climate change, and continue to suffer extensive habitat losses that reduce their ability to sequester atmospheric carbon and result in GHG emissions (Daniel A. Friess et al., 2019; Lotze et al., 2006; Waycott et al., 2009; Turschwell et al., 2021). Therefore, carbon abatement linked to BCE conservation, restoration, and creation could be integrated into project- and national-scale carbon accounting methodologies and crediting schemes (Wedding et al., 2021; Herr and Landis, 2016), promoting active management of these ecosystems as an effective climate change mitigation strategy.

In general, NCS such as blue carbon must be implemented at large scales to meaningfully reduce national emissions and contribute to Nationally Determined Contributions (NDCs). Indeed, restoration and conservation activities should be prioritised within protected or stable areas to minimise the risk of carbon leakage (i.e., permanence; Griscom et al., 2017). However, adequate protocols for monitoring, reporting, and verifying carbon fluxes within and among BCE at appropriate temporal and spatial scales can present challenges. These are due to the highly dynamic and heterogeneous nature of wetland habitats and the complexity of measuring significant carbon pools in BCE, such as the soil (Owers et al., 2018; Serrano et al., 2019; Duarte de Paula Costa et al., 2021; Ewers Lewis et al., 2020). In addition, the high costs associated with collecting field measurements make this option impractical for capturing the spatial and temporal variations of carbon stocks and fluxes at scale, strongly limiting the uptake of blue carbon strategies by industry and entrepreneurs.

The most common approach for transparent, replicable, and cost-effective reporting of green and blue carbon stocks at broad spatial scales is to use a combination of field and remote sensing data from satellites, aircraft, or vessels (Sani et al., 2019; Viscarra Rossel et al., 2014). However, the application of remote sensing for monitoring and managing NCS comes with various recognised difficulties and barriers to implementation. These include the acquisition of usable imagery, data processing, model validation, incorporation of historical perspectives, resolution of species-specific contributions to carbon storage in each habitat, and accounting for differing relationships between geomorphic and climatic zones (Ravindranath and Ostwald, 2008a; Young et al., 2021). Moreover, submerged BCE (i.e., seagrass meadows) are particularly challenging to monitor, especially in areas where the water depth where seagrasses thrive exceeds the limits of optical remote sensing instrumentation or where water clarity is poor (Barrell et al., 2015; Veettil et al., 2020). Advances in remote sensing are helping overcome some of these barriers. Challenges remain with implementing modern remote sensing, including higher costs, the need for greater technical knowledge, computational power and cloud processing, and inequitable access to data and resources. Other challenges of remote sensing are not resolvable, such as the limited spatial and temporal coverage before the Landsat satellite program (1972). In contrast, others can be successfully overcome with the increasing availability of remote sensing technologies.

IPCC Guidelines for National GHG Inventories in Wetlands (IPCC, 2014) give directions on developing blue carbon inventories. Yet, these documents lack details on integrating remote sensing for better monitoring, reporting, and verifying blue carbon assets. Thus, we designed this review to complement IPCC guidelines and discuss current opportunities for incorporating cost-effective and scalable remote sensing methodologies into blue carbon accounting frameworks. First, we briefly present the standard IPCC guidelines for national GHG inventories. Second, we discuss traditional remote sensing techniques and present promising technological innovations to improve current methods for mapping blue carbon assets. Third, we summarise different approaches to translating habitat maps into carbon estimates. Fourth, we present a decision tree to guide the choice of the most suitable method based on the spatial extent, budget, and the desired accuracy of the blue carbon assessment.

2. IPCC guidelines for carbon inventories

2.1. Framework for carbon inventories

Carbon inventories constitute the basis of reported national carbon assets and estimate net annual changes in GHG emissions (tonnes of carbon dioxide equivalents per hectare; tonnes CO_2-eq ha^{-1}) by summing positive (emissions) and negative (removals) fluxes for each carbon pool at small (project level) or large (national level) geographic scales. The IPCC provides guidelines for estimating carbon in each land-use sector (IPCC, 2006). All signatories of the United Nations Framework Convention on Climate Change (UNFCCC) must submit regular GHG emission inventories according to these guidelines: annually for industrialised countries or every 3–5 years for developing countries. In particular, chapter 4 of the 2013 IPCC Wetlands Supplement (IPCC, 2014) gives specific recommendations for estimating carbon fluxes in mangrove forests, tidal marshes, and seagrass meadows, which were lacking in the earlier 2006 IPCC Guidelines (IPCC, 2006).

2.2. Types of carbon pools in BCE

For accounting purposes, the two main classes of carbon pools are biomass and soil organic carbon (SOC; Fig. 1). Biomass pools are further subdivided into living above-ground biomass (AGB), living below-ground biomass (BGB), deadwood biomass (DB), and litter (L). AGB is particularly predominant in mangrove forests and tidal marshes, covers woody and herbaceous matter, and includes stems, stumps, branches, bark, seeds, and foliage. BGB mainly consists of living roots. DB refers to all woody, non-living biomass standing, lying, or below ground. L covers all non-living biomass that is larger than soil organic carbon (usually taken as >2 mm) but smaller than deadwood (usually meaning <10 cm).

A carbon inventory tracks changes in GHG fluxes for a land-use type (ΔC_{LU}) summed across the five carbon pools described above (biomass subpools + soil) for the years of interest, calculated as:

$$\Delta C_{LU} = \Delta C_{AGB} + \Delta C_{BGB} + \Delta C_{DB} + \Delta C_{L} + \Delta C_{SOC} \tag{1}$$

In some circumstances, harvested wood products (HWP) are included as a sixth carbon pool in reported national carbon inventories. However, this HWP pool is more often inferred from AGB (Ravindranath and Ostwald, 2008a).

Soil organic carbon is the largest pool in BCE, accounting for between 68% (mangroves) and 98% (seagrasses) of the total organic carbon (Fig. 1B and references therein), and includes everything that cannot be classified as AGB, BGB, DB, or L. Carbon burial rates, defined as the sedimentation rates of organic carbon within the soil, are much higher in BCE (100–200 g C m^{-2} year^{-1}; Fig. 1B) than terrestrial ecosystems such as tropical, boreal, or temperate forests (1–10 g C m^{-2} year^{-1}; Mcleod et al., 2011). Also, BCE can accumulate inorganic particles and organic carbon in their soils for centennial to millennial scales without reaching saturation (McKee et al., 2007; Kelleway et al., 2017), whereas terrestrial soils typically sequester organic carbon only for decades to centuries (Chambers et al., 2001; Mcleod et al., 2011). Although controversy still exists, soil organic carbon content in BCE does not always follow the typical decline with increasing soil depth and age, and that the organic carbon within the top section of BCE soils remain in a steady state owing to the continuous soil accretion (Mcleod et al., 2011; Belshe et al., 2019).

Although the standard UNFCCC framework calculates soil organic carbon stocks for the top meter of soil, BCE can have deeper stocks reaching up to 11 m in thickness accumulated over 6000 years (McKee et al., 2007; Lo Iacono et al., 2008; Mcleod et al., 2011; Kelleway et al., 2017). As a result, estimates of soil organic carbon stocks in BCE are underestimated and deeper soils should be included for more accurate accounting (Kauffman et al., 2020; Sasmito et al., 2020). IPCC accounting includes burial rates of soil organic carbon in BCE, calculated either as the whole inventory accumulated over a certain period (e.g., the last 100 years for modelling Global Warming Potential with a time horizon of 100 years under the IPCC), or after discounting the top section of the soil until organic carbon stabilizes (Johannessen and Macdonald, 2016). These choices about the period of accumulation or whether to discount the top soil can affect the estimates of burial rates of soil organic carbon in BCE by orders of magnitude (Johannessen and Macdonald, 2016).

2.3. Framework for estimating carbon flow

There are two approaches to estimating carbon: the "carbon stock-difference" (or "stock change") approach and the "gain-loss" approach (Ravindranath and Ostwald, 2008a; IPCC, 2019; McRoberts et al., 2018). The "carbon stock-difference" captures temporal changes using the ratio of carbon stocks for different land-use types at successive points in time; for example, between consecutive years ($\Delta C_{LU,\ from\ year\ 1\ to\ year\ 2}$). This approach is generally restricted to situations with established sampling programs, which are still rare for BCE. This review will focus on the carbon "gain-loss" approach, as it is simpler and easier to apply for remote and inaccessible BCE. This approach tracks the net balance of carbon additions and removals at each land-use type by multiplying *activity data* (i.e., the area of human activities resulting in emissions or removal of carbon during a specific period; km^2) with *emission/removal factors* (i.e., GHG fluxes associated with different land-use types; CO_2-eq km^{-2} y^{-1}). Activity data quantify the area converted to other land-use categories by human activities, such as deforestation or afforestation, which are often calculated using remote sensing (IPCC, 2006). Emission/removal factors estimate carbon fluxes associated with changes in land coverage and use, such as carbon gains from afforestation and carbon losses from deforestation (IPCC, 2006). The standard way to estimate changes in carbon flow (CO_2-eq y^{-1}) is to multiply these terms, as below:

$$\textit{Carbon flow} = \text{emission/removal factors} \times \text{activity data} \tag{2}$$

When choosing which emission/removal factors to consider, IPCC guidelines classify the associated methodological complexity using a three-level hierarchical tier system, which is subdivided into three approaches (IPCC, 2006). In this context, a tier is a unit of methodological detail. A shift from lower to higher tiers corresponds to increased complexity, data requirements, financial and technical commitments, and ultimately an assumed reduction in data uncertainty. Tier 1 represents the simplest approach, relying on global emission/removal factors that apply to any country (Olivier and Peters, 2005; McRoberts et al., 2018). Using Tier 1 values minimises the need for fieldwork to generate region-specific values. It is, therefore, the cheapest and most straightforward approach, but it can produce substantial errors and is only intended for large-scale first-order estimates. Tier 2 methods employ similar equations to Tier 1, but require more regional data or field data collection to measure soil properties and estimate emission factors that are country- or region-specific (Villarino et al., 2014). Finally, Tier 3 uses spatially explicit models calibrated with site-specific data to improve the confidence and accuracy of carbon stock and flux estimates (Kurz et al., 2009). This more complex approach often includes high-resolution remote sensing, GIS-based datasets, and time series for modelling the effects of management activities on carbon fluxes within ecosystems. While IPCC encourages Tier 3 methods where feasible, many countries currently use lower-tier methods due to constraints linked to limited data, technical resources, and financing (World Bank, 2021).

Modern remote sensing techniques can produce better activity data to support higher-tier methods for GHG inventories. While the Tier framework may appear somewhat simplistic, the choice of the remote sensing technique is complex. Several approaches are available, and this review is intended to help guide the decision-making process.

3. Remote sensing for activity data of BCE

3.1. Characteristics of remote sensing approaches

Remote sensing is the science of collecting data from a distance (Schanda, 2012; Ravindranath and Ostwald, 2008b; Thenkabail, 2015; Farzanmanesh et al., 2021). Sensors are typically installed on satellites, aircraft, unmanned aerial vehicles (UAV), autonomous underwater vehicles (AUV), remotely operated vehicles (ROVs), or surface vessels or ground vehicles. They collect spectral datasets that are interpreted using validation data. Sensors of various types (optical, infrared, radar, sonar, or LiDAR) can inform on different ecosystem properties across a range of temporal and spatial scales (Bunting et al., 2018; Traganos et al., 2018; Pham et al., 2019b; A. D. Campbell and Wang, 2020; Beca-Carretero

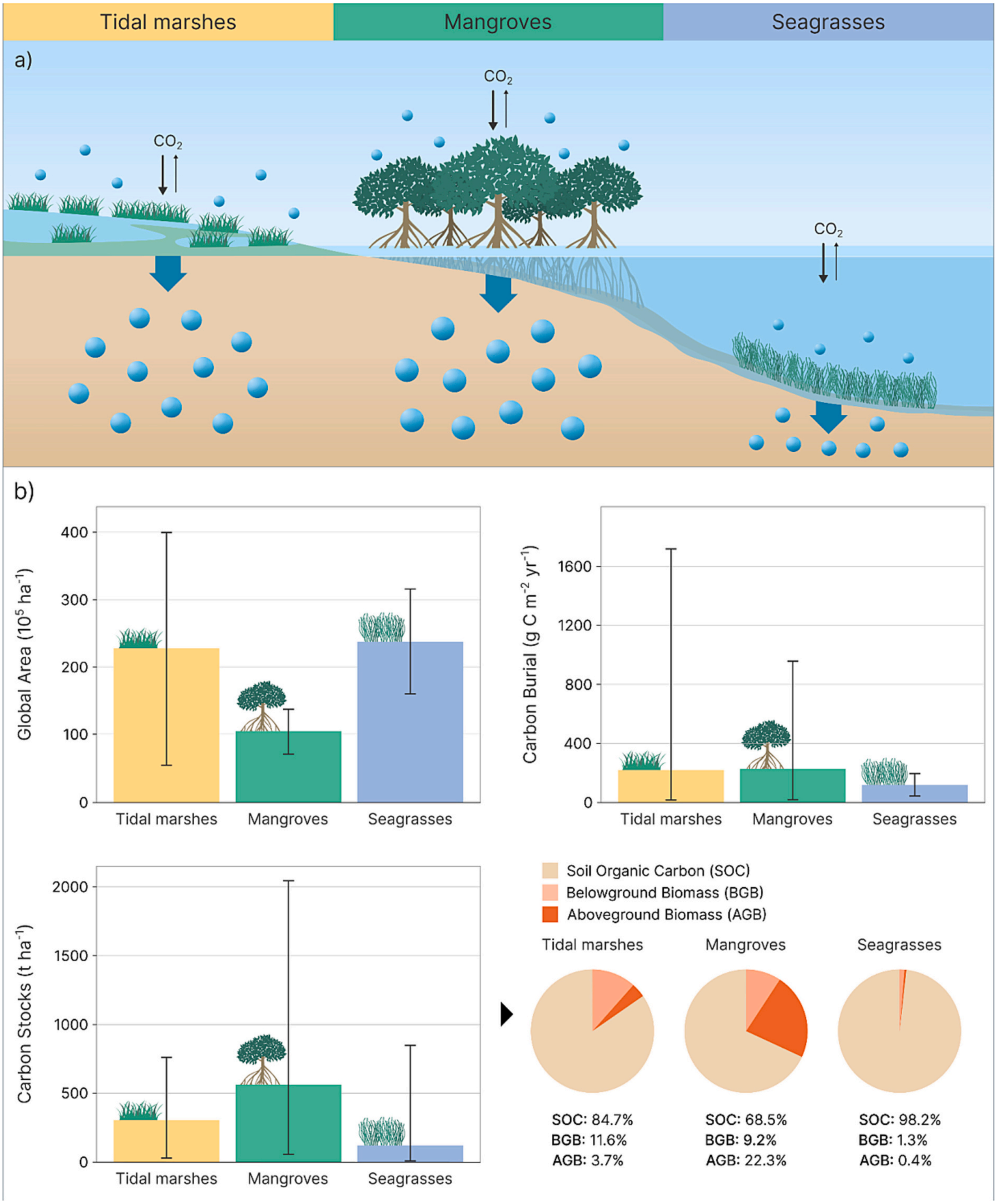

Fig. 1. a) Blue carbon ecosystems (BCE) absorb CO_2 from the atmosphere through photosynthesis and accumulate organic carbon in the biomass (both above-ground and below-ground) and in the soil. Furthermore, BCE also accumulate organic carbon from outside sources, such as from catchment run-off. Blue circles are proportional to the average trapped carbon stock in biomass and soil for each ecosystem, representing the rate of carbon draw-down. Black arrows indicate the CO_2 released back into the atmosphere through respiration. b) Summary statistics of global area (ha), carbon burial rates (g C m^{-2} yr^{-1}) and carbon stocks (tonnes ha^{-1}) for mangroves, tidal marshes and seagrasses. Error bars show maximum and minimum values typically reported in the literature. Values for soil carbon stocks, global distribution area and sequestration rates were extracted from existing blue carbon reviews (Macreadie et al., 2021; IPCC, 2014; Mcleod et al., 2011). Average values for aboveground and belowground biomass for each BCE were taken from the scientific literature (Meng et al., 2021; Collier et al., 2021; Tripathee and Schäfer, 2015; Turner et al., 2004; Brown and Rajkaran, 2020).

et al., 2020). They can capture information on biomass and soil carbon stocks (Lagomasino et al., 2016; Byrd et al., 2018; Hu et al., 2020), changes in distribution extent (Gilani et al., 2021; Lymburner et al., 2020; Lee et al., 2021), and potential carbon emissions (Crooks et al., 2018) for these different ecosystems. Other benefits of remote sensing include (1) extrapolation of in situ data to larger sites or regions (T. E. Fatoyinbo and Armstrong, 2010); (2) a large-scale overview of 3D metrics for topographic properties, such as areal extent and canopy cover and height, all of which influence carbon stocks in the landscape (Lymburner et al., 2020; Asbridge et al., 2019; Serrano et al., 2016; Hickey et al., 2021; M. Lyons et al., 2015); and (3) measurements that can be easily replicated to quantify temporal dynamics (Cohen and Lara, 2003).

Three main characteristics define the different classes of remote sensors: (1) the type of sensor, its spectral range and resolution; (2) the spatial resolution and the area covered by each pixel; and (3) the temporal resolution and duration of its historical time series (Fig. 2). First, sensors can be either passive or active. Passive sensors are more common and detect reflection, refraction, and radiation of background energy (light, heat, or sound). Values from each band (individually or pooled into indices) can underpin models of coastal land cover, including anthropogenic land use, geomorphology, habitat type, and condition. Active sensors use an artificial energy source and measure the reflectance of this energy as it interacts with land and seascapes. The reflected spectral signature and the time difference between transmission and reception provide a three-dimensional habitat model to represent structural and volumetric features on land and in water. Other than habitat extent, these sensors can also inform on habitat conditions, such as vegetative water content, canopy density and the thickness of the vegetation cover (Schanda, 2012; Ravindranath and Ostwald, 2008b; Thenkabail, 2015; Farzanmanesh et al., 2021). By relying on an inbuilt energy source, active sensors have the advantage of working at night and being less affected by cloud cover or other changes in atmospheric conditions. Both active and passive sensors are available in various designs and configurations tailored to different platforms and altitudes (or water depths) – from hand-held sensors to satellites – with different spatial and temporal scales, and spectral resolutions.

The second characteristic of remote sensing is the spatial resolution of a sensor, which determines the ground cover area of each pixel and the total spatial extent of the scene. Drones can provide very high resolution (e.g., in centimetres), while commercial satellites offer <1 m resolution (e.g., QuickBird, WorldView-3). The best freely available satellite data is Sentinel-2 with a 10 m pixel or Landsat data with a 30 m pixel (Fig. 2).

The final key characteristic of any remote sensing data is the temporal duration of the sensor deployment. This refers to the duration and

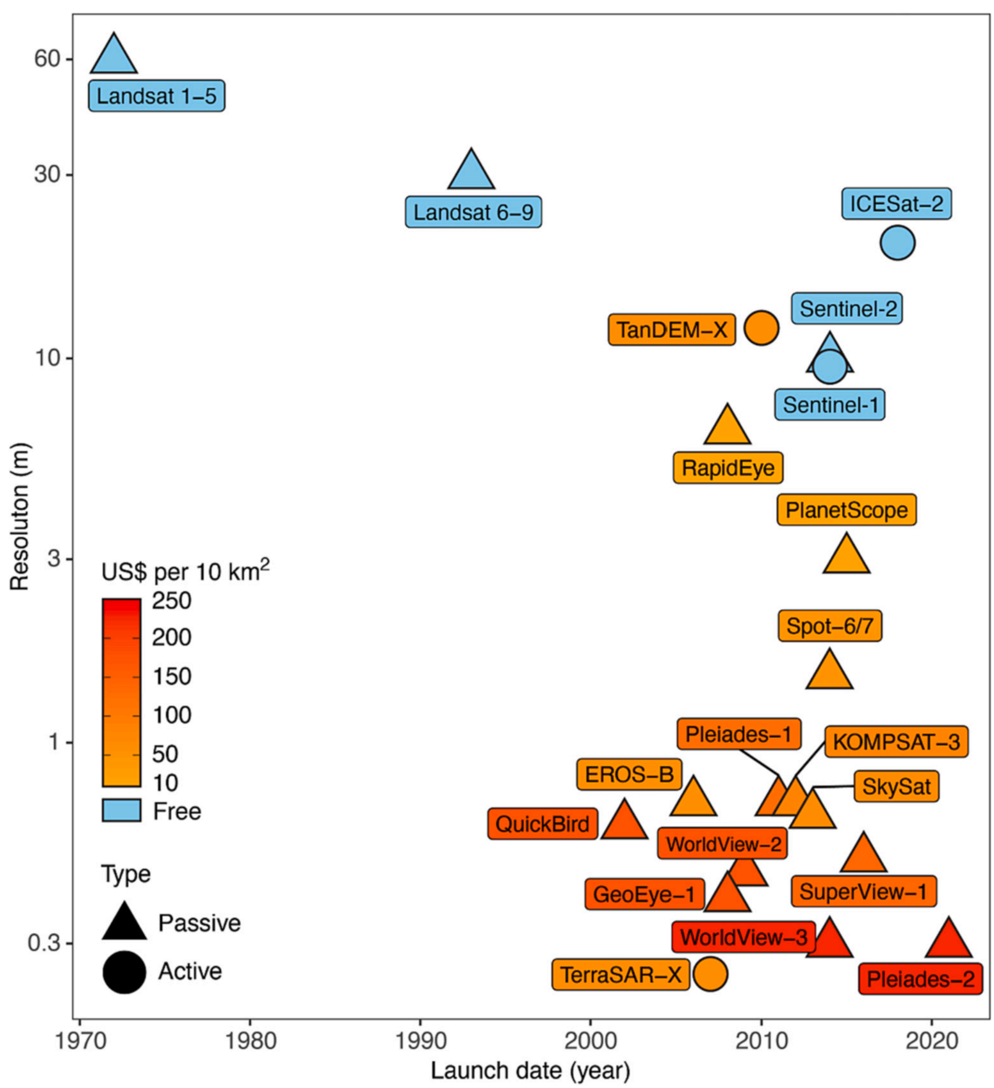

Fig. 2. Launch date and resolution of the most common satellite sensors used for remote sensing and mapping. Each point represents a satellite programme, whose colour indicates the cost for accessing the imagery (free or commercial), and the shape indicates the type of sensor (passive or active).

frequency of the available time series since the programme's launch. For example, the Landsat programme, while having among the lowest resolution, offers the longest temporal coverage of satellite imagery of Earth (biweekly since 1972), whereas most other satellite programmes only offer around a decade of data (Wulder et al., 2019; Fig. 2).

3.2. Remote sensing of BCE

Due to their locations, ecosystem structures, and spectral characteristics, remote sensing is a critical tool for assessing BCE. Satellite and airborne imagery capture unique features of the landscape that enable direct and indirect quantification of BCE extent (Lymburner et al., 2020; Gilani et al., 2021; Lee et al., 2021), blue carbon stocks (Simard et al., 2018; Sanderman et al., 2018; Pham et al., 2021), carbon fluxes (Lagomasino et al., 2019; Shapiro et al., 2015), and GHG emissions (Richards et al., 2020; Adame et al., 2021; S. E. Hamilton and Friess, 2018).

Estimates of blue carbon employ a variety of approaches and may utilise either single satellite sensors or multi-sensor fusion. The majority of approaches focus primarily on stocks at a single point in time (Sanderman et al., 2018; Simard et al., 2018) and at present are more commonly used to map vegetation biomass in mangrove forests (Sanderman et al., 2018; Simard et al., 2018; Pham et al., 2021) because sensing technologies are generally more effective at monitoring mangroves compared to other blue carbon systems. For example, satellite methods to distinguish mangrove forests from different land-use types often reach accuracies >80% (Pham et al., 2018a, 2018b; Pham et al., 2019a), whereas monitoring of tidal marshes and seagrass meadows is considerably less accurate due to limitations in separating these classes from other land cover types (Joyce et al., 2018; Phinn et al., 2018). Detecting submerged or intertidal habitats requires correcting for tides, waves, water clarity, and sun glint, in addition to the standard corrections already required for terrestrial systems (e.g., atmospheric and radiometric corrections and cloud cover). Distinguishing among land cover types with similar spectral signals is also an obstacle, as is mitigating visibility barriers due to clouds, aerosols, smoke, haze, or low light. Despite these challenges, recent advances in satellite sensor technology and greater data availability are increasingly enabling useful blue carbon estimations in tidal marshes, seagrass meadows, and mangrove forests (Sanderman et al., 2018; Simard et al., 2018; Pham et al., 2021), as outlined below.

Remote sensing tools, sensor types, and community access are continually improving. A surge in new software tools and data platforms has enabled open access to decades' worth of analysis-ready data (i.e., data that have been pre-corrected and standardised using best-practice data management; (Dhu et al., 2017). Cloud computing initiatives, such as Google Earth Engine, allow greater computational power and analytical sophistication to be used for data analysis without downloading large volumes of Earth's observational data (Yancho et al., 2020). These innovations have substantially improved the ability to map BCE, in particular, tidal flats (Murray et al., 2019) and seagrass meadows (Traganos et al., 2018; Traganos and Reinartz, 2018a, 2018b; Poursanidis et al., 2020). Access to a library of global commercial imagery has also led to the worldwide mapping of marine habitats, albeit with varying levels of uncertainty (Allen Coral Atlas, 2022).

These technological advances, together with multi-sensor fusion, big data integration, and machine learning artificial intelligence (AI) algorithms, are leading to new approaches that offer BCE models with improved accuracy and precision. For example, methods that combine spectral information from passive sensors (visible and near-infrared spectra) with the structural and density information obtained from active sensors (radar, LiDAR) have greatly improved our understanding of the spatial distribution of blue carbon (Hickey et al., 2018). Such combined usage of multi-sensor information has been successfully applied to rotation monitoring of mangrove forests, capturing annual changes in above-ground carbon stocks over 30 years (Lucas et al., 2021). Similarly, integrating remote sensing with the growing archive of on-the-ground blue carbon data enables better-informed modelling and quantification of blue carbon stocks (Duarte de Paula Costa et al., 2021; Ewers Lewis et al., 2020; M. A. Young et al., 2021). Lastly, modern AI algorithms – such as deep learning convolutional neural networks, random forests, and support vector machines, among others – continue to enhance our use and accuracy in interpreting satellite imagery for monitoring BCE (Pouliot et al., 2019).

3.3. Mapping mangrove forests

Mangrove forests have some of the highest carbon sequestration rates on Earth and provide several essential ecosystem services (Daniel A. Friess et al., 2020). Although most of their carbon is stored below the surface, a significant portion is found above ground in the trees, where it can be detected from space. These forests are typically large enough to be detected using freely available, mid-resolution (10–30 m) remote sensing imagery such as that from Sentinel-2 or Landsat. Many research programmes utilise these image databases to quantify the extent of mangrove forests over space and time. The Landsat archive offers nearly biweekly global imagery since 1972 and is one of the most widely-used remote sensing datasets for such mapping exercises (Gilani et al., 2021; Lymburner et al., 2020; Pham et al., 2019a, 2019b). This long-running satellite programme has led to numerous advances in our understanding, particularly regarding global and regional extents of mangroves and rates of mangrove forest decline over the last several decades (Goldberg et al., 2020; S. E. Hamilton and Friess, 2018; S. E. Hamilton and Casey, 2016; Gandhi and Jones, 2019; Buitre et al., 2019). Hence, Landsat imagery is the recommended option for mapping mangrove forest dynamics at large scales (>1000 ha) over half a century (Fig. 3).

A critical limitation of Landsat imagery is its spatial resolution. Because of the nominal 900 m^2 coverage of each pixel (or 3600 m^2 before 1993), smaller patches of mangrove forest may not be readily identifiable; or could contain a mixture of habitats, especially when those habitats are fringing waterways below sensor resolution. Thus, classifying mangrove species or distinguishing between mangroves and other non-mangrove tree species (e.g., palm trees) can be complicated, particularly at small scales for local carbon projects (Kamal et al., 2014, 2015). However, Sentinel-2 satellite imagery, with its superior spatial resolution of 10–20 m (depending on the spectral wavelengths used), provides opportunities to resolve forest patches along waterways or differentiate among species at large scales (Mondal et al., 2020; Liu et al., 2021; Li et al., 2019). Sentinel-2 imagery can therefore improve species identification, and estimates of above-ground biomass (D. Wang et al., 2018; L. Wang et al., 2019; Thakur et al., 2020; Maurya et al., 2021; Phiri et al., 2020; Pham et al., 2019a, 2019b), but the shorter temporal coverage of Sentinel-2 (since 2015) compared to Landsat limits its retrospective application. However, it provides important future opportunities for measuring the extent and biomass of slow-growing mangrove forests, estimating the associated carbon stocks in the biomass, and inferring stock change and accumulation rates in soil carbon. Hence, Sentinel-2 is the recommended option for more details assessments of spatial extent, density, and species compositions for mangroves at smaller scales (e.g., 100–1000 ha; Fig. 3).

Very high-resolution satellite imagery can help estimate several otherwise inaccessible features of mangrove forests and their carbon stocks. Recent applications include the estimation of specific biophysical parameters of mangrove forests, such as species distribution (Rahman et al., 2019; Qiu et al., 2019; Zhu et al., 2015), leaf-area indices (Heenkenda et al., 2015; Pu and Cheng, 2015; Kamal et al., 2016), leaf chlorophyll (Heenkenda et al., 2015), nitrogen content (Zhang et al., 2012; Flores-de-Santiago et al., 2013; Zhang et al., 2013; Fauzi et al., 2013; Axelsson et al., 2013), and canopy height (Simard et al., 2018; Lagomasino et al., 2015, 2016). These newer satellites can provide essential information for local-scale projects. Still, there are also drawbacks to using very high-resolution imagery, such as increased costs for

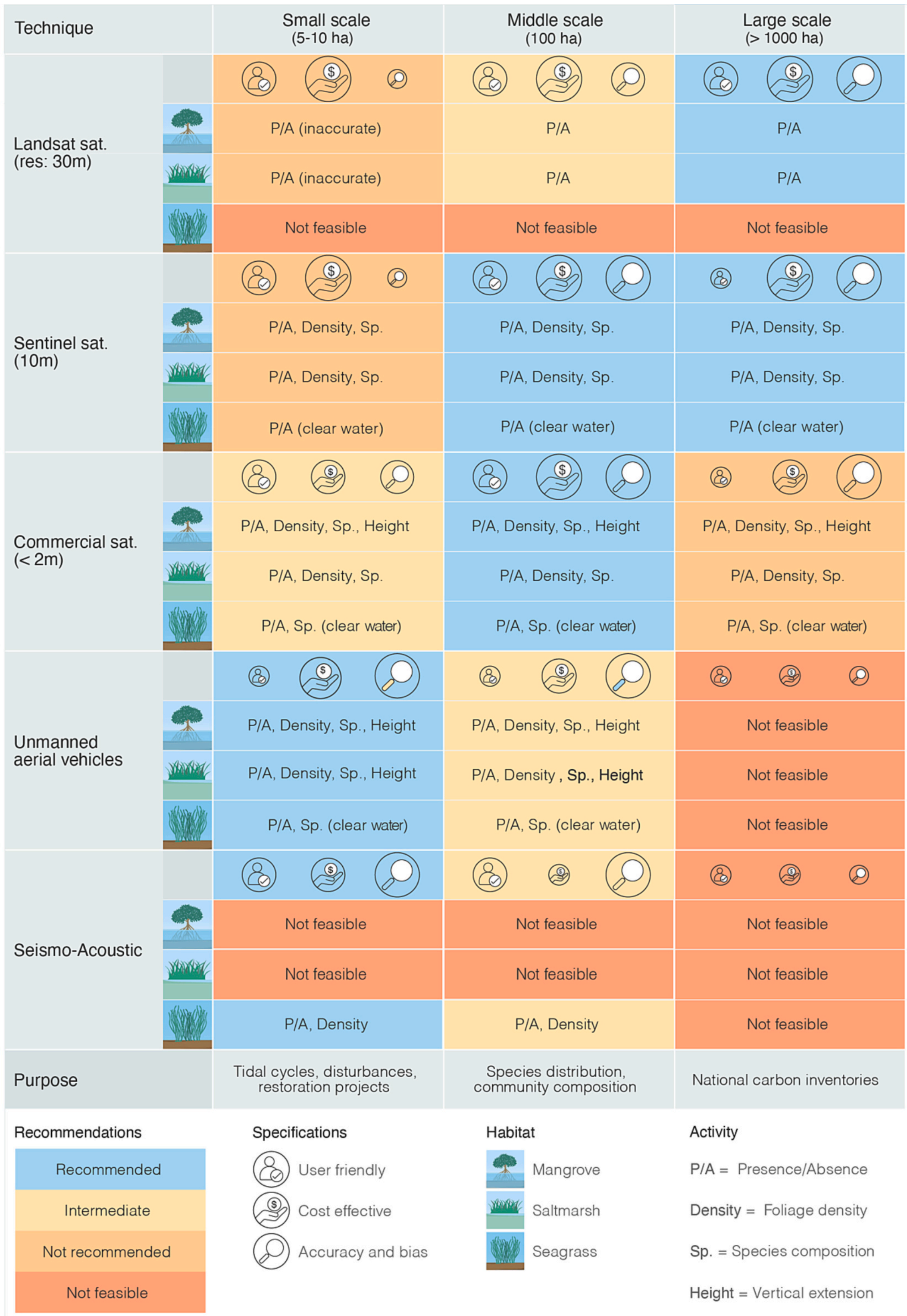

Fig. 3. Summary of recommended remote sensing techniques (rows) and their applicability for mapping blue carbon ecosystems (row icons) at different scales (columns). Symbols indicate other key characteristics of each application, with larger sizes showing greater benefits for the associated task. We list typical remote sensing activities for each combination.

data acquisition and requisite processing power. These factors can sometimes outweigh the benefits of higher prediction accuracy for blue carbon projects (Lu, 2006). Many high-resolution sensors also omit shortwave-infrared bands (e.g., QuickBird, GeoEye, WorldView-3), which are important for differentiating vegetation areas and estimating their above-ground biomass (Lu et al., 2016; Kumar et al., 2015; Gleason and Im, 2011). However, using datasets at increasingly higher resolution is often not a requirement for carbon accounting and can increase countries' dependency on external technical assistance. Nonetheless, these more sophisticated datasets help capture more information on a system and lowering uncertainties in the estimates. Hence, commercial satellites are often recommended for assessing mangrove properties at small scales (5–100 ha; Fig. 3).

Globally, a significant proportion of mangrove forests is in tropical regions where high evaporation rates can lead to dense cloud formations, making satellite imaging of these forests difficult with traditional optical sensors. In these areas, active sensors that emit and capture reflected light, such as Synthetic Aperture Radar (SAR), have demonstrated several capabilities that passive sensors cannot, including the ability to acquire data under all weather conditions and the ability to interact with various parts of the vegetation canopy (reviewed by Sinha et al., 2015). Their capacity to "see through clouds" and capture information on habitat structural characteristics, therefore, offers promise in helping to ensure continuous data coverage in high cloud cover areas (Thomas et al., 2015; Pham et al., 2018b).

Other active approaches, such as airborne LiDAR (laser imaging, detection, and ranging), are the gold standard when measuring height properties of mangrove forests (Wannasiri et al., 2013), and help reduce the uncertainty in above-ground biomass (Asner et al., 2011). Recent LiDAR sensors include the Global Ecosystem Dynamics Investigation (GEDI) sensors onboard the International Space Station and the Advanced Topographic Laser Altimeter System (ATLAS) instrument on ICESat-2. These modern sensors are helping to improve the precision and accuracy of mangrove canopy height and above-ground biomass estimations (Stovall et al., 2021; Ghosh et al., 2020; T. Fatoyinbo et al., 2021). Upcoming satellite missions, such as NASA-ISRO Synthetic Aperture Radar (NISAR) and Surface Water and Ocean Topography (SWOT), will further enhance our ability to map coastal wetlands (Adeli et al., 2021) and capture height-dependent changes within mangrove forests, which will be an important factor for monitoring, reporting, and verifying blue carbon stocks.

3.3.1. Promising directions: UAV for high-resolution mapping of mangrove forests

While satellites are beneficial for assessing BCE at large scales, projects at smaller scales (5–100 ha) would benefit from on-demand remote sensing using UAV. Compared to satellites, UAV can provide finer details of the land without the complications of having to correct for atmospheric conditions or clouds (Sheridan, 2020; Emilien et al., 2021; Hsu et al., 2020; Ruwaimana et al., 2018), although they do require radiometric calibration to maintain spectral consistency over time. They can also be deployed more frequently and fit-to-purpose (for example, to capture event-based changes to BCE) with minimal cost. Several studies have already used UAV to map above-ground biomass of all types of BCE: mangrove forests (Otero et al., 2018; J. A. Navarro et al., 2019; A. Navarro et al., 2020), tidal marshes (Doughty and Cavanaugh, 2019; Doughty et al., 2021), and seagrass meadows (Chayhard et al., 2018; Sousa et al., 2019). Thus, UAV is one of the recommended options for small-scale monitoring of many BC ecosystems (Fig. 3).

Whereas mangrove forests have been mapped with a high degree of accuracy for decades using freely available remote sensing data from satellites (e.g., Landsat or Sentinel-2), using UAV for small-scale monitoring of mangrove forests has important benefits. UAV-based carbon estimates can become nearly indistinguishable from field-based carbon estimates derived from on-site measurements of height, basal diameter, stem diameter, and average canopy diameter and, in many cases, enables the scalability of such data (Otero et al., 2018; A. Navarro et al., 2020; Li et al., 2019). Yet, obtaining high accuracies and precisions with UAV also requires substantial field measurements to quantify site-specific characteristics of forest type, biomass, and carbon stocks. UAV can reduce costs by approximately US$ 35,000 per hectare relative to on-ground measurements (A. Navarro et al., 2020). Limitations due to weather conditions and flight policy restrictions might hinder data collection using UAV, but they nevertheless have considerable potential for mapping BCE at local scales. We expect that studies combining UAV data with satellite-based imagery will further increase the accuracy and scale of blue carbon estimation (Qiu et al., 2019).

3.4. Tidal marsh mapping

Since the release of the IPCC 2013 Wetlands Supplement, some governments (e.g., the U.S. and Australia) have begun to supplement their national GHG inventories with data on emergent coastal wetlands, such as tidal marshes, as these can represent a significant carbon stock (Duarte et al., 2013; Serrano et al., 2019; IPCC, 2014). Nevertheless, these habitats are highly dynamic, and it is challenging to document their temporal variability (D. A. Friess et al., 2012). Remote sensing could prove a cost-effective and replicable approach to monitoring changes in the above-ground biomass of tidal marshes across multiple temporal and spatial scales.

Typically, the vegetation of tidal marshes is variable, with the habitat divided into discernible patches ranging from a few square metres to tens of square metres, with a single plant species dominating each patch (a phenomenon known as "zonation"; (Guimond and Tamborski, 2021). These patches also vary in elevation, meaning there are gradients in vegetation densities (i.e., vertical zonation; (Townend et al., 2011). Mapping tidal marshes must consider multiple spatial gradients and heterogeneities, spanning from tens of centimetres to various kilometres. These areas are also subject to frequent flooding and changes in water levels, resulting in additional small-scale temporal changes in vegetation coverage and species composition with potential consequences for carbon storage (Macreadie et al., 2013). As a result, frequent high-resolution imaging over several years is recommended to capture tidal marshes' temporal and spatial variability accurately.

In the past, remote sensing for tidal marshes used satellite data at medium resolution (10–30 m) to broadly determine various characteristics: presence/absence, vegetation type, or differentiation among a limited number of species (Smith et al., 1998; K. Brown, 2004). With advances in remote sensing technology, monitoring efforts have increasingly relied on airborne sensors such as LiDAR to produce digital elevation models and map vegetation height (Pham et al., 2019a). However, LiDAR can only provide structural information using a single wavelength in the near-infrared, which limits its ability to differentiate among plant species (J. B. Campbell and Wynne, 2011).

To better characterise plant biodiversity in tidal marshes, recent studies have increasingly used multiple spectral signatures in the visible and near-infrared portions of the electromagnetic spectrum (Adam et al., 2010). In particular, high-resolution superspectral and hyperspectral sensors from commercial satellites can collect many contiguous spectral bands (sometimes >200) with narrow bandwidths and high spatial resolution (up to 6 cm). These sensors are mounted on commercial satellites to offer data at high spatial resolutions, which may be the recommended option for mapping tidal marsh dynamics (Fig. 3). Nonetheless, one of the limitations of using modern sensors is the lack of long-term data for establishing reliable baselines. This limitation will be less of a problem in the future as these sensors accumulate longer time series. Despite these welcome technological advancements, mapping tidal marshes remains a complex task, especially where the vegetation is surrounded by other grassland and wetland habitats (Kandus et al., 2018; Gallant, 2015).

3.4.1. Promising directions: mapping tidal marshes using hyperspectral imagery

Plant types can exhibit different relationships with remotely sensed vegetation indices (Glenn et al., 2008). Whereas this has historically hindered the development of robust, empirical remote sensing models for estimating plant biomass across communities, Hladik et al. (2013) successfully combined data from multiple sensors (hyperspectral and LiDAR) to improve tidal marsh classification. However, this might not be a general solution (Hladik et al., 2013). LiDAR measurements are often too coarse to quantify the height of herbaceous vegetation in tidal marshes and consequently give unreliable biomass estimations. Collecting hyperspectral and LiDAR data from airborne sensors is also costly in terms of budget and preparation.

As a better option moving forward, modern superspectral and hyperspectral satellites offer multiple (>30) high-resolution (< 1 m) bands with wavelengths spanning from visible (400–770 nm) to infrared (750–1000 nm) and microwave (1000 to >2000 nm; Collin et al., 2018). Given that spatial resolution is more important than spectral resolution for mapping tidal marshes (Belluco et al., 2006), and because the shortwave infrared spectral range is strongly correlated with water content (Adam et al., 2010), the use of these high-resolution bands is promising for accurately monitoring the main features of tidal marshes. For example, Collin et al. (2018) trained high-resolution (0.31 m) data from 16 bands of the superspectral WorldView-3 sensor with a combination of on-ground measurements of vegetation height, airborne LiDAR soundings of ground elevation, and airborne drone blue-green-red (BGR) spectral signatures of tidal marsh components. Integrating these on-ground and air-derived measurements with WorldView-3 imagery using AI algorithms (artificial neural networks) produced one of the most accurate maps of tidal marshes to date. These results suggest that better resolving the spectral properties of vegetation, soil, and water using modern imaging technologies and AI could substantially improve the complex task of mapping tidal marshes while opening the door for novel alternatives for mapping other BCE.

3.5. Mapping seagrass meadows

Seagrasses are valuable BCE where stocks occur primarily (98%) as soil organic carbon. However, the use of remote sensing to detect seagrass meadows and define above-ground biomass (the extent and biomass of seagrass meadows) is often problematic. Seagrass habitats range from intertidal to >50 m depth, so the spectral properties are more variable and potentially weaker than those of other BCE (Gallant, 2015). Specifically, the biophysical properties of the submersed environments where seagrasses occur limit the utility of remote sensing (Green et al., 1996; Dekker et al., 2006; M. S. Hossain et al., 2015; Veettil et al., 2020; Phinn et al., 2018). Mapping this aquatic BCE remotely must therefore overcome various complexities that need to be accounted for – including water clarity, depth, small/cryptic species, and seasonal variation (Phinn et al., 2018) – and these cannot always be resolved (Holmes et al., 2007; Kendrick et al., 2008).

Nonetheless, using remote sensing imagery with multiple spectral channels can help identify the presence of seagrass meadows and monitor and detect change over time (Veettil et al., 2020), with several recent reviews on the effectiveness of different remote sensing techniques (M. S. Hossain et al., 2015; Pham et al., 2019b; Sani et al., 2019; Veettil et al., 2020). One study achieved an impressive accuracy of >90% using open-source Sentinel-2 imagery to map dense seagrass meadows in the highly transparent, shallow waters of the Aegean Sea in Greece (Traganos and Reinartz, 2018a). Similarly, Lyons et al. (2015) used high-resolution remote sensing imagery to quantify the above-ground biomass of seagrass meadows in subtropical Australia. Despite these successes, remote sensing techniques are often inadequate for determining the benthic composition because seagrasses, macroalgae, and even corals can appear similar spectrally; particularly in deeper waters where the red absorption of chlorophyll decreases (Cho, 2007; M. B. Lyons et al., 2012).

One way to improve identification accuracy is to use hyperspectral imagery. As exemplified above, this more recent technology can collect a wide range of spectral wavelengths at a fine resolution, thus allowing for better discrimination among seagrass species (Dekker et al., 2006). In addition, hyperspectral imagery is helpful in identifying benthic components, water column turbidity, and additional parameters such as the seagrass leaf index (H. M. Dierssen et al., 2010; Heidi M. Dierssen et al., 2019). However, it is important to appreciate that any airborne or satellite remote sensing comes with limitations when detecting seagrasses in deep or turbid water, with maximum detectability depending on sensor type, wind disturbance, sun glint, and water quality.

To better document seagrass meadows in habitats inaccessible with satellites, remotely operated vehicles (ROV) can be equipped with optical sensors and GPS tracking to monitor seagrass coverage (Mohammad Shawkat Hossain and Hashim, 2019; Yamamuro et al., 2002). These semi-automatic systems can record high-quality images to accurately monitor seagrass density and species distribution (Ouchra and Belangour, 2021). However, this technology has been rarely used for seagrass, is expensive, and is mainly designed for small-scale mapping.

Overall, it is likely that field-based mapping methods, including camera-based sleds and tows or ROV, will remain the most effective way of mapping seagrasses, particularly in deeper water and where species are small or cryptic, and in shallow waters with high turbidity. In these circumstances, remote sensing can be replaced with a combination of modelling approaches and field-based ground-truthing (Coles et al., 2009; Carter et al., 2021).

3.5.1. Promising directions: seismo-acoustic techniques for seagrass meadows

Side-scan sonar uses sound propagation to measure distance. Acquiring underwater videos using sonars has been widely used to map underwater seagrass meadows at small and mid-scales (5–100 ha; Komatsu et al., 2003; Greene et al., 2018). This approach allows for overcoming the time-consuming and expensive processes of field calibration and ground-truthing involving scuba diving or ROV (Pergent et al., 2017). Nonetheless, side-scan sonar remote sensing techniques cannot map seagrass soil carbon stocks and have limited capacity to detect low levels of above-ground biomass – such as those commonly encountered in most deepwater habitats. While deepwater seagrass species (e.g., *Halophila* spp.) have low above-ground biomass, they form sizeable below-ground carbon stocks (York et al., 2018, 2020).

As an alternative to side-scan sonar, high-resolution seismo-acoustic imaging is emerging as a promising technique to estimate soil carbon pools associated with underwater seagrass meadows. These modern echosounders (e.g., Innomar SES-2000 compact) emit narrow beams at low frequencies that can penetrate several metres below the seafloor at high vertical and horizontal resolution (M. F. Hamilton and Blackstock, 1998). The acquired seismo-acoustic profiles are then deconvolved and corrected for energy loss. The seafloor and sub-seafloor layers are identified to accurately estimate the volume of organic-rich soils based on soil lithology, porosity, density, fluid saturation, and compaction characteristics (Hamilton and Blackstock, 1998). Hence, this type of remote sensing has the potential to document not only seagrass extent but also biomass and soil carbon pools (Chassefière et al., 1974; Lo Iacono et al., 2008). Multibeam sonar technologies can also detect disturbances in seagrass beds, such as the extent of overgrazing of urchins and implications for sediment erosion (Carnell et al., 2020).

Although applying these cutting-edge seismo-acoustic techniques to blue carbon research is in its infancy, preliminary outcomes show great potential for the method to be a robust, non-destructive, cost-effective, and scalable solution for estimating carbon pools in underwater BCE. Seismic data has been used in combination with bio-stratigraphic and lithological data to reconstruct estuarine infilling processes and the evolution of delta formations (Bastos et al., 2010; Morley, 2011; Palamenghi et al., 2011), both of which are key processes driving past and future carbon storage in BCE. Earlier studies based on seismic technologies managed to successfully identify superficial seagrass layers (Rey and Diaz del Rio, 1989). Still, the combined use of modern, high-resolution multibeam echosounders and on-ground data (biomass and soil cores) now enables seagrass extent and carbon stocks to be estimated at high resolution over large spatial scales (Lo Iacono et al., 2008; Monnier et al., 2020, 2021).

Advances in seismo-acoustic technologies over the last decades, driven by the oil and gas industry and other commercial applications, have unlocked new opportunities to explore deep carbon sinks in BCE. This technique could dramatically reduce the need for costly and time-consuming on-ground campaigns for mapping seagrass meadows, offering quantification of organic biomass and soil carbon pools beyond the typically-reported one-metre soil depth benchmark. However, these techniques would need to be verified with deep-water seagrass communities, which have small above-ground biomass but make up a globally significant carbon pool (York et al., 2018, 2020). To our knowledge, seismo-acoustic techniques have never been applied to study blue carbon in mangrove forests and tidal marshes. Yet, this technology has the potential for a novel quantification of soil carbon in the unconsolidated soil layers of floodplains or mangrove swamps (Uko et al., 2016). Further research into applying seismo-acoustic techniques in BCE will likely improve our ability to cost-effectively quantify organic content in BCE soils, monitor changes in soil carbon stocks, and estimate accumulation rates at large spatial scales. Overall, the ability to "see through cloudy water" makes seismo-acoustic techniques the recommended option for most assessments of seagrass dynamics at small to medium scales (e.g., 5–100 ha; Fig. 3).

4. Decision tree for estimating blue carbon

Following Eq. (2), estimating blue carbon stocks using the carbon gain-loss approach requires two types of information: activity data (i.e., data on the area of a human activity resulting in emissions; km^2) and emission/removal factors (i.e., data on GHG fluxes; CO_2-eq km^{-2} y^{-1}). In this section, we present a decision tree for estimating blue carbon based on: (1) the choice of a remote sensing technique for activity data; and (2) the choice of methodological complexity for emission/removal factors (Fig. 4).

We will begin by asking which type of remote sensing should be used to estimate activity data. Many satellite sensor types can quantify the extent and change of BCE (which enables the calculations of carbon content). Still, we will limit our discussion to freely available optical imagery from Landsat and Sentinel-2 satellites, commercially available high-resolution (HR) imagery (e.g., QuickBird, WorldView-3), and locally-collected UAV and ROV imagery. The spatial image resolution will define the smallest discernible feature or the minimum mapping unit (MMU). In the case of BCE, we have already seen that mangrove forests are more readily mapped from space, whereas tidal marshes and seagrass meadows present more of a challenge. An individual tree canopy can be observed with UAV or commercial satellite imagery but would not be captured by Sentinel-2 or Landsat due to their lower spatial resolution.

With this in mind, the first of four considerations when deciding the appropriate type of remote sensing is to assess the purpose of the exercise. The relevant approach for large-scale (national) carbon inventories is fundamentally different from that for small-scale carbon accounting projects. A national carbon inventory, as specified on page 8 of the 2006 IPCC Guidelines for National Greenhouse Gas Inventories, should be unbiased and "contain neither over- nor under-estimates so far as can be judged" (IPCC, 2006). In contrast, carbon accounting projects—including REDD+ and others aligned with the Verified Carbon Standard (VCS)—are more conservative and deal with uncertainty by choosing values that are probably lower than the actual figures (Needelman et al., 2018). Hence, using low- or mid-resolution remote sensing is cost-effective for unbiased estimation of blue carbon stocks at national scales because local over- and under-estimates can be assumed to average out at larger scales. Small-scale carbon projects require high- or very high-resolution remote sensing data to reach acceptable precision for certified Verified Carbon Units (VCU) and to be financially sustainable (Shapiro et al., 2015).

The second aspect to consider is the need for historical baselines. The Paris Agreement under UNFCCC developed a legally binding commitment to reduce GHG emissions relative to 1990 levels for national inventories. Strictly meeting this commitment requires a time series since

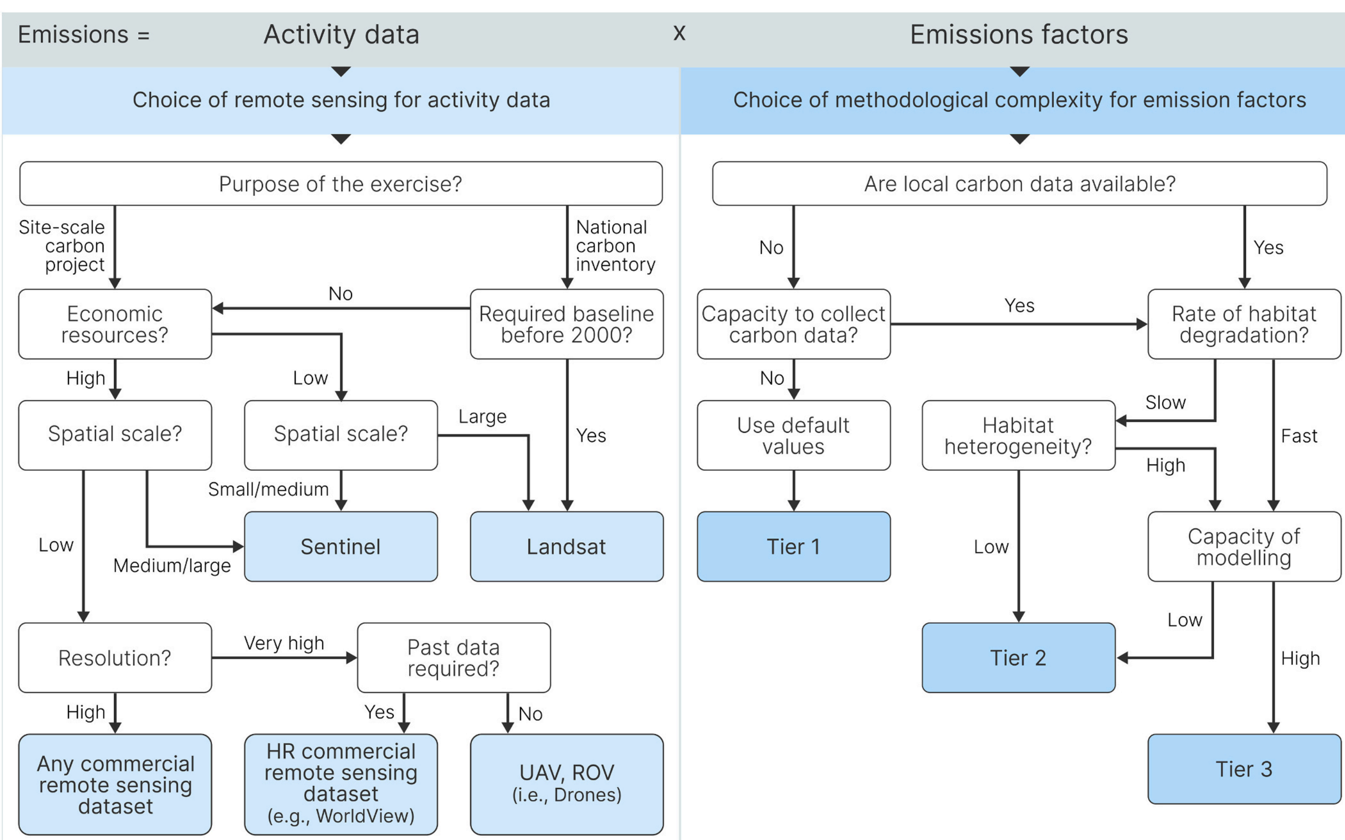

Fig. 4. Decision tree for estimating carbon stocks for BCE following the carbon gain-loss approach. The start of the process (top of diagram) represents Eq. (2). The left-hand side guides the remote sensing technique for estimating activity data, and the right-hand side aids the choice of estimating emission factors.

at least 1990, which strongly limits remote sensing choices and makes Landsat one of the few available satellite sources. For individual carbon projects, the baseline is often the habitat condition at the start of operations, without any need to document previous years. In these cases, very high-resolution satellites or UAV campaigns may be the most cost-effective approaches. Moreover, carbon projects are typically developed on small to medium spatial scales, meaning purchasing and elaborating high-resolution maps is economically and computationally feasible. In summary, national inventories are generally constrained to those few remote sensing datasets with long-term temporal coverage. In contrast, a wider range of remote sensing techniques is available to smaller-scale carbon projects.

The third consideration is the level of mapping accuracy desired for each BCE. As explained above, mangrove forest mapping can reach very high accuracies even with open-access remote sensing data (e.g., Landsat, Sentinel-2). Mapping tidal marshes often requires higher-resolution imagery, such as QuickBird or WorldView-3. The submerged nature of seagrass meadows makes them more difficult to map using satellite remote sensing (especially in deep, turbid water or for highly patchy meadows), complicating their inclusion in carbon inventories despite the high carbon stocks stored within them. As a result, estimating carbon stocks in seagrass meadows often requires data from underwater ROV, census or sensors (e.g., seismo-acoustic techniques).

The fourth aspect to consider is the temporal and spatial variability of the habitat. Habitats that are changing rapidly (e.g., seagrass meadows and tidal marshes, with a timeframe of months to years) require more frequent analysis of remote sensing imagery than slow-growing habitats (e.g., mangrove forests, on the scale of years to decades). Similarly, habitats with high spatial heterogeneity or under high anthropogenic pressure, such as those near highly populated areas, would benefit from more frequent high-resolution monitoring.

After selecting the remote sensing technique for collecting activity data, a second decision must be made on the level of methodological complexity for translating habitat maps into blue carbon stocks (i.e., for measuring emission/removal factors). Approaches range from using default emission factors (Tier 1 approach) to nation-specific factors (Tier 2) to modelling (Tier 3). This choice is firstly influenced by the capacity to access published measurements of local carbon stocks (e.g., the Coastal Carbon Atlas, https://ccrcn.shinyapps.io/CoastalCarbonAtlas/) or collect local novel field data, which is a requirement for Tiers 2. Tier 3 goes beyond local emission factors and involves detailed time series of carbon fluxes within ecosystems feeding into a modelling framework. Another consideration is the expected rate of human impact, with rapidly deteriorating habitats needing more complex methods (i.e., Tier 2 or 3) to achieve the requisite precision. Habitats with high heterogeneity may require a Tier 2 or 3 approach to capture their increased spatial variability. Finally, moving from a Tier 2 to a Tier 3 approach requires higher-level skills for modelling and remote sensing. Tier 2 or 3 are often needed when monitoring carbon projects associated with financial rewards. In contrast, no such requirement applies to national inventories (although developed countries are expected to report at higher levels than Tier 1).

5. Future pathways and overall recommendations

The UNFCCC's Paris Agreement aimed to establish legally binding commitments to reduce GHG emissions, with the monitoring of carbon sinks and sources constituting a key aspect of the agreement. Therefore, BCE management should be essential to global actions to tackle climate change. These ecosystems play a crucial role in global biogeochemical cycles through their ability to sequester and store large volumes of organic carbon. The most cost-effective means of mapping BCE and tracking their performance as carbon sinks is to use remote sensing techniques. Therefore, evaluating the progress of each state signatory of the Paris Agreement in following their commitments relies on methods to convert remote sensing data into carbon estimates. In this respect, several challenges remain, particularly with mapping complex and less visible ecosystems such as seagrass meadows.

Nonetheless, newer satellites offer higher-resolution worldwide coverage than earlier technologies (e.g., Landsat) and are rapidly being incorporated into blue carbon accounting. Commercial high-resolution imagery is increasingly used for local-scale projects, but purchase costs remain an important limitation. In addition, these modern options have less than a decade of historical coverage. The short temporal coverage of modern sensors affects the reliability of baseline estimates and reduces the ability to quantify rates of change. Nonetheless, we have identified UAV and seismo-acoustic techniques as promising alternative tools for ongoing development. However, despite these promising developments, much of the world's subtidal seagrasses remain challenging to capture with any of these techniques. Many are small in stature, occur in optically deep or turbid waters and are beyond the effective discrimination of these techniques. Yet these inconspicuous systems have disproportionate effects on organic carbon stocks and cannot be ignored in Blue Carbon inventories (York et al., 2018, 2020).

It is worth noting that our analysis of BCE excludes macroalgae such as kelp forests. Macroalgae are the dominant primary producers in vast coastal ocean areas and cover an estimated 25% of the world's coastlines (Wernberg et al., 2019). However, there is considerable uncertainty over their global carbon sequestration magnitude, variously estimated at between 61 and 268 Tg CO_2-eq y^{-1} (Krause-Jensen and Duarte, 2016). Similarly to seagrass meadows, remote sensing applications are showing promise in quantifying this BCE (Casal et al., 2011; Arafeh-Dalmau et al., 2021; St-Pierre and Gagnon, 2020; Schroeder et al., 2019; Kwan et al., 2022), although poor water visibility remains a barrier in common with other submerged systems. Better macroalgal mapping performance demands improved spatial, temporal, and spectral resolution in remote sensing imagery but also requires a robust framework to correct for tides, currents, waves, and other environmental variables (Schroeder et al., 2019). Macroalgal beds can often extend beyond the capabilities of optical sensors and the use of swath mapping systems – such as multibeam sonars combined with remote video observations for ground truth – are effective mapping techniques at large (>100 s Km^2) scales (M. Young et al., 2015). Finally, one innovative approach to improve mapping in shallow, clear water conditions is crowdsourcing to identify putative macroalgal forests from satellite imagery (e.g., floatingforests.org; Rosenthal et al., 2018), which could also provide a viable model for quantifying other BCE. Yet, involving citizen scientists is often impractical, as it requires high user participation, it is limited to simple tasks, and can lead to high variability in the assessments.

As newer sensors become available with greater temporal and spatial resolutions, it is increasingly urgent to develop ways of integrating modern imagery and older data into a single time series with variable resolution. For example, the Landsat programme has been the only source of biweekly global imagery since 1972, but at a much coarser resolution (30–60 m) than more modern satellite sensors (1–5 m). It will be increasingly beneficial to develop techniques to combine and cross-calibrate time series across sensors with different resolutions and historical coverages to draw new inferences (Filgueiras et al., 2020; Teo and Fu, 2021; Gao et al., 2006; Burkhalter et al., 2005). However, techniques to merge time series from different sensors are in their infancy and have several limitations. For example, harmonising data among sensors often implies downscaling images and only using the coarser resolution. An important area for future research is to improve these techniques so that they can better take advantage of all available information.

With the recent 27th UN Climate Change Conference of the Parties (COP27) Summit in Sharm el-Sheikh having renewed international interest in climate change mitigation, it is increasingly recognised that BCE can play a crucial role in our portfolio of Nature-based Solutions (NbS). These solutions include actions targeting societal challenges, such as climate change, food and water security, biodiversity, human health, and disaster risk mitigation. Among these, management solutions specific to decreasing atmospheric carbon are known as Natural Climate Solutions (NCS). Here, we have summarised existing and emerging remote sensing techniques, illustrating how they can help develop accurate and cost-effective carbon inventories and track carbon stocks' spatial and temporal dynamics at local, regional, national, and global scales. While there are now several very effective techniques to monitor mangrove forests using freely available mapping resources, other BCE (including tidal marshes and seagrass meadows) still await further developments that can overcome the issues of technical limitations, higher costs, and computational demand. Nonetheless, the scientific literature already documents several successful use cases for remote sensing that cover all BCE, thereby underpinning the considerable potential of this approach for habitat mapping and carbon accounting. The next challenge is to identify and focus on the most promising approaches (including techniques to merge time series from older, low-resolution but long-term sensors with newer, higher resolution but shorter-term sensors) and work towards making them available to governments, industry, corporations, and communities alike, in a concerted global effort to map, conserve and restore BCE.

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

The data shown in Figures 1 and 2 are available in a public repository (Mendeley Data, doi: 10.17632/ygwrwtryz2.1).

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