Remote Sensing in Ecology and Conservation Open Access

ORIGINAL RESEARCH

Earth observation for ecosystem accounting: spatially explicit national seagrass extent and carbon stock in Kenya, Tanzania, Mozambique and Madagascar

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Keywords
Blue carbon stock, East Africa, ecosystem accounting, Google Earth Engine, seagrass, Sentinel-2

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Editor: Vincent Lecours
Associate Editor: Gang Zheng

Received: 10 December 2021; Revised: 25 March 2022; Accepted: 29 April 2022

doi: 10.1002/rse2.287

Abstract

Seagrass ecosystems are globally significant hot spots of blue carbon storage, coastal biodiversity and coastal protection, rendering them a so-called natural climate solution. Their potential as a natural climate solution has been largely overlooked in national and international climate strategies and financing. This stems mainly from the lack of standardized, spatially explicit mapping and region-specific carbon inventories. Here, we introduce a novel seagrass ecosystem accounting framework that harnesses machine learning, big satellite data analytics and open region-specific reference data within the Google Earth Engine cloud computing platform. Leveraging a biennial percentile composite, assembled from 16 453 Sentinel-2 surface reflectance image tiles at 10-m spatial resolution, and 20 820 reference data points, we applied the cloud-native framework to produce the first national inventories of seagrass extent and total seagrass carbon stocks in Kenya, Tanzania, Mozambique and Madagascar. We estimated 4316 km^2 of regional seagrass extent (mean F1-score of 59.3% and overall accuracy of 84.3%) up to 23 m of depth. Pairing country-specific in situ carbon data and our spatially explicit seagrass extents, we calculated total regional seagrass blue carbon stocks between 11.2–40.2 million MgC, with the largest national carbon pool in Kenya (8–29.2 million MgC). We envisage that improvements in the remote sensing components of the framework guided by a necessary influx of region-specific data on seagrass stocks and fluxes could reduce uncertainties in our current spatially explicit ecosystem extent and carbon accounts, enhancing the incorporation of seagrasses into Multilateral Environmental Agreements for future resilient ecosystems, societies and economies.

Introduction

Seagrasses, the overlooked nature-based solution

Seagrass ecosystems—intertidal and subtidal vegetated coastal habitats—along with mangroves and tidal flats are globally acclaimed as natural climate solutions (NCS) due to their significant ecosystem services which include carbon sequestration, biodiversity maintenance and coastal protection. Although covering less than 0.5% of the global seascape, NCS mitigate around 3% of annual global greenhouse gas (GHG) emissions (Macreadie et al., 2021; Nellemann et al., 2009). However, the immense ‘blue carbon’ sinks of seagrasses have long remained underestimated and overlooked in climate agendas and schemes (Duarte et al., 2013; UNEP-WCMC & Short, 2020). The Paris Agreement of 2015 put forth the Nationally Determined Contributions (NDCs) to streamline the conservation and restoration of NCS based on quantified GHG removals. From the 160 countries featuring seagrasses, only 12 have explicitly included them in their mitigation and/or adaptation strategies by October 2021 (United Nations Environment Programme, 2020a). This notable exclusion arises from the lack of standardized, spatially explicit seagrass monitoring and carbon inventories and hampers effective blue carbon policy actions, especially in nations with vast seagrass carbon sinks (Macreadie et al., 2019, 2021).

The globally significant East African seagrasses

Stretching over 25 degrees of latitude and 18 degrees of longitude within the Tropical Indo-Pacific —the world's most extensive and diverse seagrass bioregion—East Africa hosts 12 seagrass species (Green & Short, 2003; McKenzie et al., 2020; UNEP-WCMC & Short, 2020). These tropical and subtropical seagrasses lie often in close proximity to mangroves, tidal flats and corals, building ecologically interconnected seascapes (Gullström et al., 2018; Huxham et al., 2018; Juma et al., 2020). These natural architectures protect and enhance seagrass ecosystem services with co-benefits for societies and economies, often beyond their physical locations. For example, seagrasses in Gazi Bay, Kenya store 620 000 Mg of carbon with an estimated climate regulation value of $19 million globally (Githaiga et al., 2017; United Nations Environment Programme, 2020a, 2020b). These carbon stocks have fueled the world's first carbon crediting scheme which bundles seagrass services with mangrove conservation (Githaiga et al., 2017; United Nations Environment Programme, 2020a, 2020b). In addition, seagrass meadows provide nursery habitats for fish and food provisioning to local communities (Nordlund et al., 2018; Unsworth et al., 2019), protection from cyclones and stabilization of seabed sediments and cultural services which elevate the sense of identity for local fishers and communities (de la Torre-Castro & Rönnbäck, 2004).

Challenges for East African seagrass ecosystem services

These highly valued seagrass ecosystem services are yet facing numerous challenges. More frequent and intense tropical storms, rising thermal stresses and sea level, coastal eutrophication and development, overfishing and seaweed farming are all impacting seagrass health and the livelihoods of their dependent coastal societies (Amone-Mabuto et al., 2017; Côté-Laurin et al., 2017; Cullen-Unsworth et al., 2014; Eklöf et al., 2008; United Nations Environment Programme, 2020a, SMART Seas, 2021). These threats are coupled with uneven levels of protection: only Madagascar recognizes the climate change mitigation and adaptation benefits of seagrasses, while Tanzania only recognizes their adaptation potential (Herr & Landis, 2016). Zooming out to the tropical Indo-Pacific bioregion, despite being the world's largest seagrass bioregion, only 17% of its seagrass exist within present marine protected areas (MPAs) (McKenzie et al., 2020; United Nations Environment Programme, 2020a).

Contemporary Earth Observation advances to the rescue

Until today, there have been numerous multi-scale mapping efforts using satellite data in the broader East Africa (Dahdouh-Guebas et al., 1999; Gullström et al., 2006; Harcourt et al., 2018; Knudby et al., 2010, 2014; Knudby & Nordlund, 2011; Poursanidis et al., 2021; Teixeira et al., 2015). More recently, in 2020, the Allen Coral Atlas project achieved the first regional geomorphic and benthic habitat mapping using PlanetScope mono-temporal mosaics (Allen Coral Atlas, 2021). With the exception of the latter, which focus in the first 10 m of depth, all other studies focused mainly on local benthic habitat mapping.

The aforementioned challenges for East African seagrasses paired with the broader lack of scalability and spatial inventories can be resolved by harnessing contemporary Earth Observation advances: cloud computing, big satellite data analytics, artificial intelligence and openly available data (i.e. satellite image archives, field-collected and citizen-derived observations) (Traganos, 2020; United Nations Environment Programme, 2020a). Cloud-native Earth Observation frameworks are the next generation of decision support systems for coastal ecosystems (Bunting et al., 2018; Lyons et al., 2020; Murray et al., 2019; Nijland et al., 2019; Traganos, Aggarwal, et al., 2018). These scalable frameworks can integrate and transform petabyte-scale satellite and geospatial datasets on-the-fly to Analysis Ready Data (ARD) (Dwyer et al., 2018). Such transformed data are built on multi-temporal (MT) analytics to overcome showstoppers in traditional coastal aquatic remote sensing using single images: dense clouds, waves, varying atmospheric and water column composition, sunglint, etc. (Poursanidis et al., 2021; Thomas et al., 2021; Traganos, Aggarwal, et al., 2018; Traganos & Reinartz, 2018). Through their high scalability, repeatability and confidence, these modern big data paradigms can enable transparent, spatially explicit accounts of seagrass ecosystem extent, condition and services, from local to global level.

Ecosystem accounting and study objectives

Ecosystem accounting (EA) is a coherent and holistic quantitative framework that entails the aforementioned accounts across space, time and human activities. EA frameworks can provide physical and monetary measurements (accounts) on the ecosystem extent (total area), condition (e.g. depth, water quality), services (e.g. carbon sequestration, biodiversity support) and assets (stocks and their changes) (United Nations 2021; Weber, 2014). Despite the EA requirements for spatially explicit data to enable their policy uptake, these approaches for coastal NCS like seagrasses are still exploratory (Chen et al., 2020; Weatherdon, 2018; Weatherdon et al., 2017). Here, our central objective is to produce the first nationwide accounts of seagrass extent and total carbon stocks for Kenya, Tanzania, Mozambique and Madagascar. To achieve this, we designed and applied a novel Google Earth Engine-native seagrass ecosystem accounting framework, leveraging 2 years of Sentinel-2 surface reflectance data and multi-sourced in situ and human-annotated reference datasets.

Materials and Methods

Study site

The East African seascape covers more than 128 000 km^2 across a coastline of 21 924 km (WRI, 2000). Its coastal climate is classified as Aw/As (tropical savanna climate) according to the Köppen-Geiger classification system (Beck et al., 2018); with the exception of the southeast Madagascar coast—BSk (cold semi-arid climate) and Af (tropical rainforest climate). The seasonality here is characterized by a bi-modal precipitation system with two wet seasons between March and May, and during October and December, set apart by two dry seasons from June to September and during January and February (Bornemann et al., 2019). The seascape of the region features an estuarine and coastal system of frequently co-occurring blue carbon keystone ecosystems—12 seagrass species (10 in Kenya, Tanzania and Madagascar), up to 9 mangrove species, and at a much smaller extent, salt marshes, extending from the intertidal zone up to 40 m of depth (UNEP-Nairobi Convention and WIOMSA, 2015). According to the best available information in all four studied countries, seagrasses cover 7098 km^2, while mangroves extend across 7215 km^2 (Bunting et al., 2018; UNEP-WCMC and Short, 2020).

Data

Satellite data

We utilized all satellite imagery from the Sentinel-2 (S2) Level-2A (L2A) Surface Reflectance archive as was available at the initiation of our study (14 December 2018–20 April 2020) within the Google Earth Engine (GEE) platform. This archive featured 33 095 100x100-km S2 tiles across 128 743 km^2 in East Africa and comprised the initial satellite data input to our cloud-native ecosystem accounting framework.

Reference data

We collated three individual reference datasets on turbidity, bathymetry and benthic habitats to guide the model training and validation in our framework. The collation was based on a combination of field-collected and visually self-annotated data points. The field datasets were sourced from several efforts across the four countries, while the annotated points were based on the S2 data. We describe our image annotation approach and benthic habitat data characteristics in sections 2.3.1 and 2.3.2. Table 1 depicts the type, nature of collection, temporal range, total number of points and location of the three reference datasets with associated sources, where available. Table S1 shows the ratios of our utilized bathymetry training to validation data across different depth intervals.

Cloud-native coastal ecosystem accounting framework

Our cloud-based ecosystem accounting framework consists of three main technological components (Fig. 1) enabled and guided by big satellite and reference data: (a) the Optically shallow processor (2.3.1), (b) the Machine learning architecture (2.3.2) and (c) the Seagrass ecosystem accounting (2.3.3).

Optically shallow processor

First, this technological component integrates and combines recent developments in multi-temporal composition and scalability, optically deep water (areas with no emanating signal in the water surface from the seafloor) and turbidity masking (Pertiwi et al., 2021; Poursanidis et al., 2021; Thomas et al., 2021; Traganos, Aggarwal, et al., 2018; Traganos, Poursanidis, et al., 2018). Here, it used the 33 095 raw Sentinel-2 L2A tiles ingested by GEE within the area of interest and filtered them for cloud coverage using the GEE *filterMetadata* function, retaining only tiles with less than 25% CLOUDY_PIXEL_PERCENTAGE, which halved the raw archive to 16 453 S2 tiles. These tiles were then the input to the MT analytics processor which first uses the Quality Assurance band of each image to remove pixels flagged as clouds, before employing the *reduce* function to compose all of the scenes to the 20th percentile value per pixel. This results in an image composite for the entire East Africa. The 20th percentile has been proven qualitatively superior to both

Table 1. Collated reference datasets.

Type	Method of collection	Time range	Number of Points	Country	References
Turbidity	Human annotation	2017–2020	360	All	This study
Bathymetry	In situ collection	2014, 2016, 2017, 2018, 2019	2590	Tanzania, Mozambique	Eggertsen (2019), Muaves (2019), Teixeira et al. (2015), Macia et al. (2017)
Benthic Ecosystems	In situ collection and human annotation	2014–2020	17 870	All	Borrego-Acevedo et al. (2020), Muaves (2019), Teixeira et al. (2015), Poursanidis et al. (2021), Macia et al. (2017)

All in the Country column denotes Kenya, Tanzania, Mozambique and Madagascar.

median (50th percentile) composites and traditional single-image approaches (Donchyts et al., 2016; Traganos, Aggarwal, et al., 2018; Traganos, Poursanidis, et al., 2018; Traganos & Reinartz, 2018). The advantage of MT analytics in coastal aquatic remote sensing analysis is the highly automated and effective parallelization of three processes: (a) the filtering of common redundancy in single image approaches: very bright and very dark artifacts over coastal regions (e.g. remaining atmospheric scattering, clouds, sunglint, turbidity, waves, cloud shadows); (b) the large-scale scalability of a seamless, spectrally homogeneous image composite and (c) the circumvention of the effect of varying tidal ranges by utilizing the darkest 20% of reflectances which is the quantitative analogue of a modelled low-tide composite (Sagar et al., 2017) minus the computation burden. This scalability enabled by GEE is essentially the main innovation of our ecosystem accounting framework.

Second, the percentile composite is masked for land and optically deep water pixels utilizing a non-parametric, highly adaptive algorithm (Donchyts et al., 2016) based on a combined Otsu-based thresholding (Otsu, 1979) and Canny edge filter applied to the modified normalized difference water index, MNDWI (Pertiwi et al., 2021; Thomas et al., 2021; Xu, 2006). The MNDWI index integrated the green (B3; 560 nm) and shortwave infrared (B11; 1610 nm) bands of the Sentinel-2 L2A percentile composite. Due to the large geographical scale of the percentile composite and the spatially restricted nature of the Canny edge filter, we applied the unsupervised algorithm twice: first, to differentiate exposed land from subtidal coastal waters, and second, to disentangle optically shallower from optically deeper water pixels. Both differentiations were attained by automatically identifying suitable local threshold values on the bimodal histograms of the MNDWI index. Finally, we employed a recently developed turbidity processor to detect and mask medium to high turbidity pixels by applying spectral unmixing on the percentile composite aided by the annotated data points described in section 2.2.2 and Table 1. An in-depth description of the turbidity processor is given in Pertiwi et al. (2021). The utilization of this pre-processing step was deemed necessary due to high reflectances (bright targets) caused by yearlong, persistent turbidity across the entire East Africa, remnants of the MT composition. These pixels contain little to no benthic signal, comprising optically deep and thus redundant for our analysis. Table S4 provides the accuracy assessment of our thematic regional turbidity layer. The output of the optically shallow processor is an optically shallow, above-surface reflectance (Rrs) composite: essentially, a synthetic ARD image consisting of pixels free of atmospheric, water surface and water column effects.

Machine learning architecture

The pre-processed S2 Rrs percentile composite, including the B1-B5 (443–705 nm) bands, along with 17 870 reference data points were the input to the second technological pillar of our framework: the cloud-native Machine learning (ML) architecture. This architecture classifies national benthic ecosystems including seagrasses. We collated a reference inventory of 13 547 points (10 789 for training and 2758 for validation) based on a combination of recent field data collections, and image and data interpretation covering all four countries (Table 1). To further enhance our ML architecture, we annotated 4323 additional training points in all four countries using the S2 percentile composite and the GEE-based high-resolution satellite basemap, for a total of 15 112 training points (Table 2; Fig. S1). This was to reduce initially observed misclassifications (false positives) of seagrasses as turbid waters, despite the prior masking of turbid pixels. The initial six classes of the 13 547 points reflected the main subtidal benthic ecosystems of East Africa: seagrass, coral (mainly with algae), sand, rubble, rocks and microalgal mats (Kennedy et al., 2021). As our main target here was

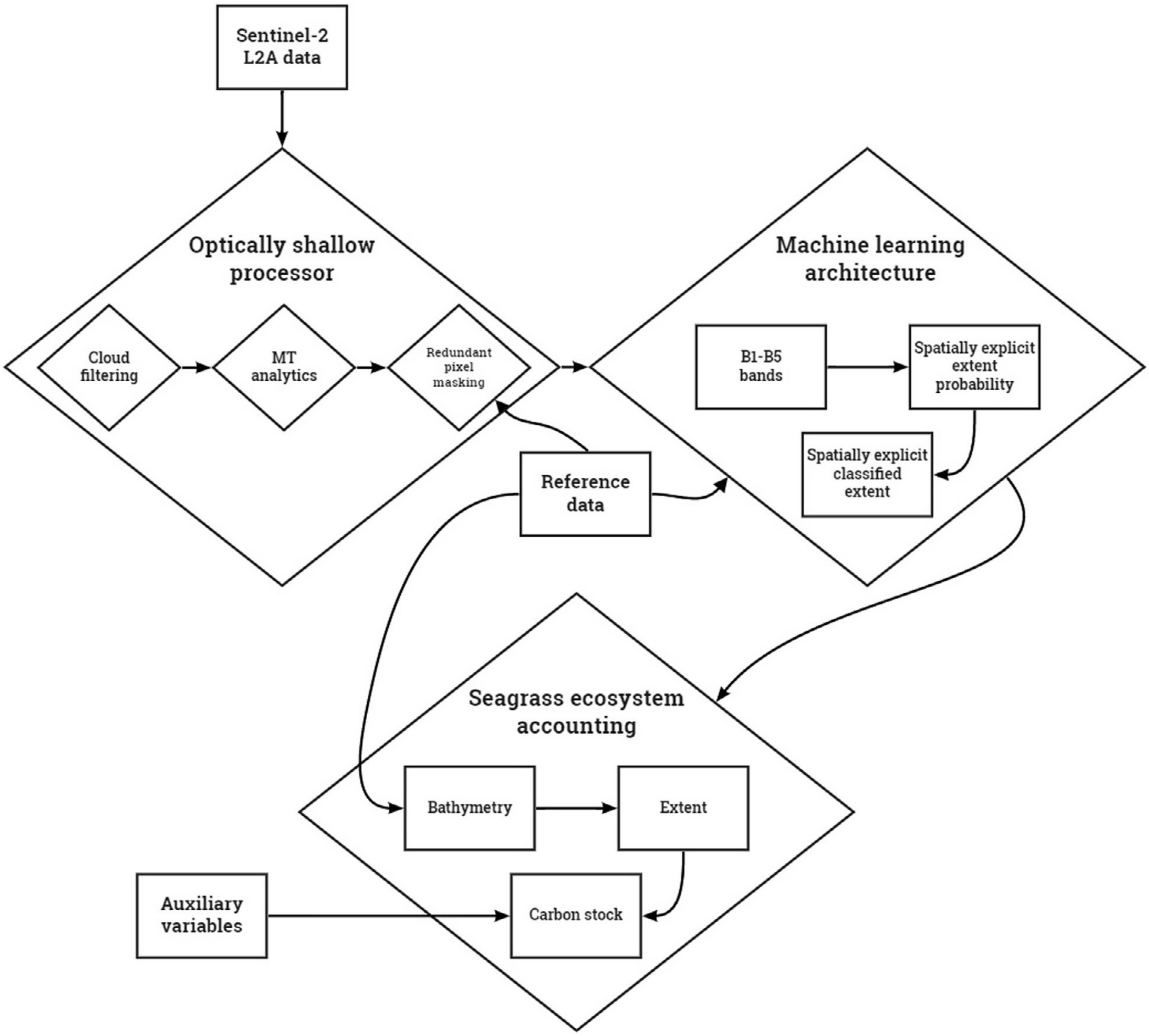

Figure 1. Schematic of the cloud-native Earth Observation coastal ecosystem accounting framework. MT analytics stands for multi-temporal analytics, which comprises the cloud masking using the QA band as well as the image stack reduction into a composite image. Readers are directed to Section 2.3.1 for more information.

to accurately classify the national seagrass extent, we reduced the six-class system into a two-class system: seagrass and non-seagrass. Figure 2 depicts the spectral ranges of the seagrass reference data per country for the first five S2 Rrs percentile bands.

The supervised ML classifier in the heart of our ML architecture is the ensemble algorithm of Random Forests (RF). Random Forest is a classification method that produces many different random decision trees, combining in turn the results of these trees based on the most popular vote (Breiman, 2001). Our choice of RF is justified by its efficiency in big satellite data processing; effectiveness to handle collinearity and nonlinearity between predictor variables; robustness against overestimates and noise in the input data. Additionally, RF featured more recently solid results in local-to-global, seascape remote sensing exercises using various optical satellite data in both local and cloud environments (Lyons et al., 2020; Murray et al., 2019; Poursanidis et al., 2019, 2021; Traganos, Poursanidis, et al., 2018; Traganos & Reinartz, 2018). We employed the *Classifier.smileRandomForest* framework in GEE, based on Breiman (2001), and trained it with our collated training data (Tables 1 and 2). Intrinsically, this function would also split the training data based on our

Table 2. Collated reference dataset utilized in the Machine Learning Architecture.

	Kenya	Tanzania	Mozambique	Madagascar	East Africa
Training data					
Seagrass	1289	1506	1612	1054	5461
Non-seagrass	1393	2526	3912	1820	9651
Validation data					
Seagrass	230	181	236	69	716
Non-seagrass	218	503	832	489	2042

This dataset was synthesized from recent field data collections and image annotation using photointerpretation, and was used for the machine learning training and validation (2.3.2).

input of 80–20 while training. We tuned three main RF parameters—*numberofTrees*: 10, *variablesPerSplit*: 2, and *minLeafPopulation*: 5. Our ML architecture consists of a two-tier approach. First, an intermediate probabilistic mode (through the GEE *setOutputMode* method) outputs the per-pixel probability of extent for the seagrass and non-seagrass classes varying between 0 and 100%, or the 'soft' probability of both classes. Second, the per-pixel classified extent or 'hard' probability of the two classes is obtained based on a dynamic thresholding analysis to identify the most accurate soft probability threshold for the classification. This dynamic analysis follows a back-and-forth, iterative process of varying the probabilities of seagrass presence in intervals of 10 between 10 and 100%, and observing resulting mapping accuracies (described in section 2.4) and classified seagrass extent, *that is* both quantitatively and qualitatively. This iteration allowed us to reduce potential misclassifications of seagrasses as turbid or optically deep waters. The output of the ML architecture is the spatially explicit nationwide seagrass ecosystem extent in Kenya, Tanzania, Mozambique and Madagascar.

Seagrass ecosystem accounting

The third and final technological pillar of our framework involves the assessment and accounting of the national ecosystem extent, ecosystem condition (bathymetry in our study) and carbon stocks (ecosystem asset) of seagrasses in Kenya, Tanzania, Mozambique and Madagascar (Fig. 1). While the classification of the seagrass extent is described in section 2.3.2, we include it here as this spatially explicit account is further delineated by estimating its satellite-derived bathymetry (SDB) (and hence depth limits)—applying the multilinear regression SDB method of Thomas et al. (2021) to the optically shallow Rrs B1-B5 bands and the depth reference points of Table 1. This assessment ensures comprehensive and consistent seagrass ecosystem extents (Fig. 3). Table S3 displays statistics of our SDB experiments using three different metrics and several S2 band combinations.

To estimate the nationwide seagrass carbon stocks, we conducted an extensive literature review of available in situ data of carbon stocks in seagrasses including total, above-ground (ABG) and below-ground (BGB) biomass and soil carbon (SC). Seagrasses sequestrate and store carbon within the living ABG (e.g. leaves, stems), BGB (e.g. roots, rhizomes) and non-living biomass (e.g. leaf detritus, macroalgae), and, principally, within their underlying soils (e.g. soil organic matter, dead plant tissues) (McLeod et al., 2011). The ratio of living biomass-to-soil carbon is approximately 1:91, while the ABG:BGB ratio is 1:2 (Fourqurean et al., 2012). Our total carbon stocks equal the sum of the ABG, BGB and SC, calculated at both national and regional level.

We calculated the national seagrass blue carbon stocks by multiplying our classified seagrass extents (in km^2) with their corresponding total carbon stock data (Mg/km^2), running both Tier 1 and Tier 2 assessments (Howard et al., 2014). This enables an intercomparison between their resulting carbon stocks, at national and regional scale. Tier 1 assessments feature the highest uncertainty and errors—up to ±50% for ABG pools and ±90% for the SC pools—as they are based on simplified assumptions and global averaged estimates (Kennedy et al., 2014). In contrast, Tier 2 assessments integrate more regional and/or country-specific mean carbon measurements which reduce the uncertainty of the globally aggregated estimates. Table 3 shows the ranges of carbon stocks used in the tiered calculations. Tier 2 is based on existing mean field-collected ranges of organic carbon (if there is more than one studied carbon stock range). Due to insufficient data in Madagascar, we adopted the same ranges from the nearest seagrass meadows of Mozambique, assuming similar carbon stock characteristics due to proximity. We articulate potential uncertainties and assumptions behind the synthesis of Table 3 data in the supplementary material, after Table S1.

Statistical analysis

We validated the accuracy of the nationwide seagrass ecosystem extent using the following statistical metrics: overall accuracy (OA), producer's accuracy (PA), user's accuracy (UA), F1-score (the harmonized mean of PA and UA) through error matrices based on 2758 validation points for both classes (seagrass, non-seagrass; Table 2; Fig. 2) and displayed in Table S2.

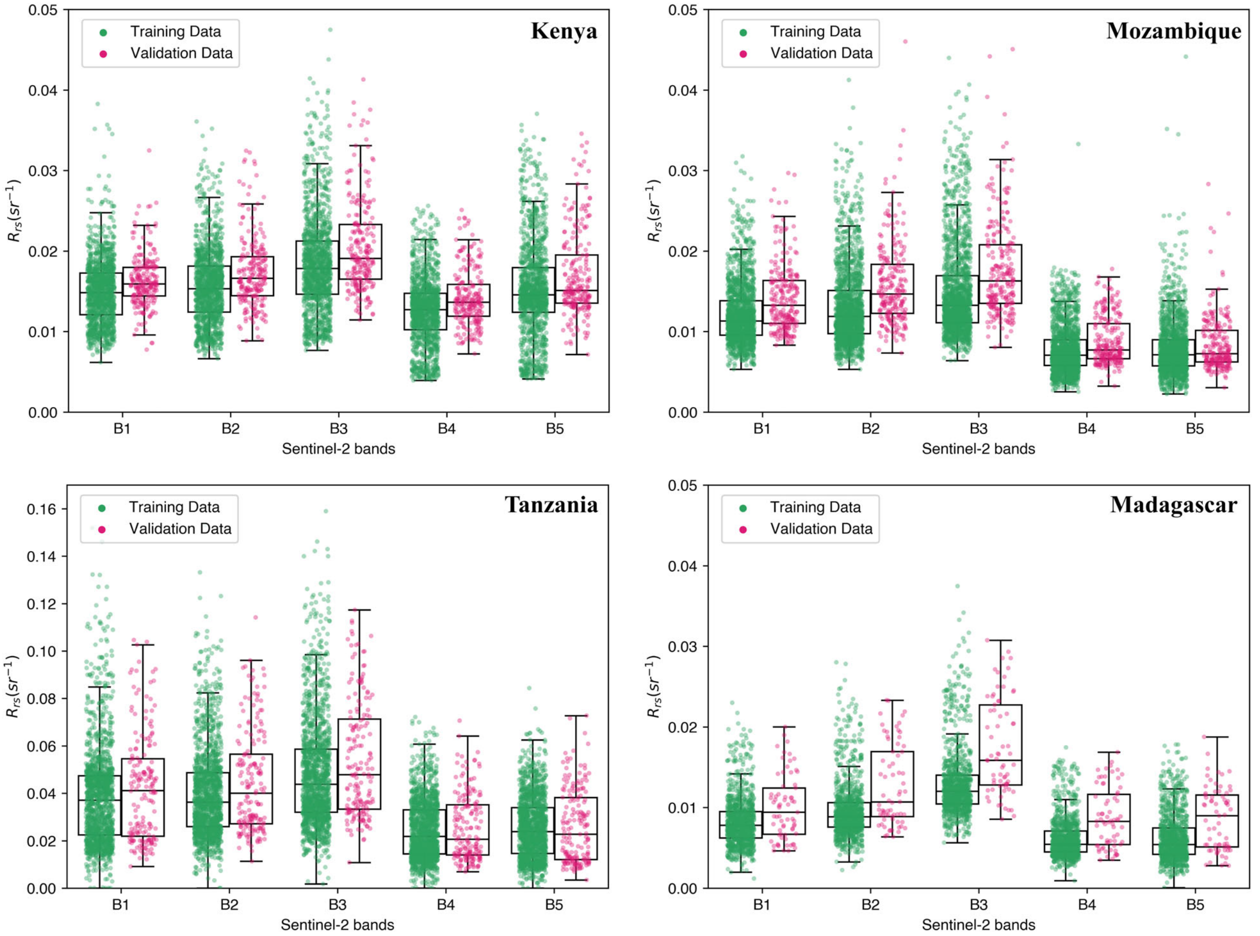

Figure 2. Spectral ranges of the utilized seagrass reference data. Ranges are shown across the first five Sentinel-2 above-surface reflectance (Rrs) bands in all four studied countries. Table 2 displays how these reference data are split between the different countries. Note the wider reflectance range in the y-axis in Tanzania in contrast to Kenya, Mozambique and Madagascar.

Results

Spatially explicit national seagrass extents in East Africa

Figure 4 displays our mapped seagrass ecosystem extent at 10 m in Kenya, Tanzania, Mozambique and Madagascar between 0 and 23 m of depth. Utilizing a threshold of 70% on the RF extent probability layer, we mapped 679.6 km^2 of extent in Kenya (14.1% of studied national scale; mean and maximum depth of 2.1 and 9.2 m, respectively); 548.2 km^2 in Tanzania (2.3% of studied national scale; mean and maximum depth of 2.1 and 23 m, respectively); 1779.3 km^2 in Mozambique (2.7% of studied national scale; mean and maximum depth of 1.6 and 9.2 m, respectively) and 1309.3 km^2 in Madagascar (2% of studied national scale; mean and maximum depth of 1.06 and 8.52 m, respectively). Our mapped seagrass extent across the entire East Africa is 4316.4 km^2 (3.4% of studied regional scale; mean and maximum depth of 2 and 23 m, respectively). The F1-score for the nationwide extents is 66.7% in Kenya (OA of 73.2%), 70.4% in Tanzania (OA of 88.1%), 55.9% (OA of 86.4%) in Mozambique and 44.2% in Madagascar (OA of 89.6%)—with an average regional F1-score and OA of 59.3% and 84.3%, respectively. The analytical error matrices can be found in the supplementary material (Table S2). The highest PA of 55.7% is observed in Tanzania, whereas the highest OA of 89.6% is observed in Madagascar.

National seagrass carbon stocks in East Africa

Using our classified extent inventories, we calculated associated ranges of national total carbon stocks of seagrasses in four countries of East Africa (Table 4). Based on the global-based Tier 1 assessment, East African seagrasses may store between 4.36 and 357.83 million Mg of carbon

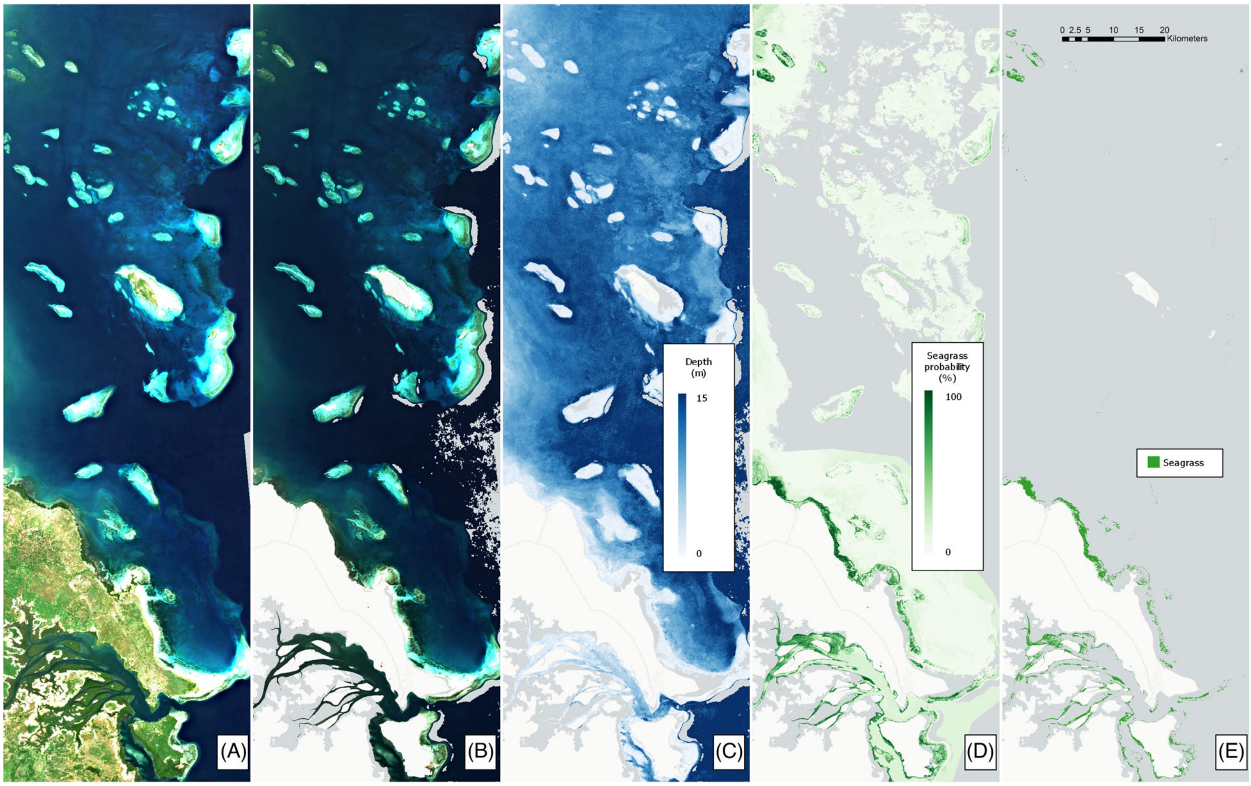

Figure 3. Successive mapping products of the ecosystem accounting framework. Displayed is the nearshore island system of the Lindi region, Tanzania. (A) 10-m Sentinel-2 surface reflectance percentile composite (natural color RGB; 2018–2020); (B) 10-m Sentinel-2 above-surface reflectance percentile composite masked for land, optically deep waters and turbid waters (natural color RGB); (C) Satellite-derived bathymetry (m); (D) Spatially explicit seagrass extent probability (0%–100%); (E) Spatially explicit Random Forest classified seagrass ecosystem extent. Readers are invited to view all these layers in our GEE app: https://aviputri.users.earthengine.app/view/mappingeastafrica.

(average of 46.62 Mg C). The country-specific Tier 2 assessment narrows down these total carbon storages between 11.16 and 40.23 million Mg. The largest national carbon storage using the Tier 2 assessment is observed in the Kenyan seagrasses which range between 7.96 and 29.25 million Mg, and represents 73% of the regional carbon storage, despite representing only 15.7% of the regional seagrass extent. It is noteworthy that all our Tier 1 national carbon stocks fall outside of the respective Tier 2 ranges. The largest overestimation is observed in Mozambique by 14.86 million Mg, while, in Kenya, the Tier 1 carbon stock is 655.97 Mg lower than our Tier 2 assessed minimum.

Discussion

National seagrass extents in East Africa

Our national seagrass extents are the first-ever products of their kind: spatially explicit in nature at 10 m/pixel, sourced from standardized, comprehensive big satellite data analytics, spanning four countries, 128 743 km^2 of seabed and 21 924 km of coastline, in previously uncharted waters for seagrasses. The uniqueness and vast geographical scale of our physical national ecosystem accounting was the product of innovative and intensive research and development, but is characterized of a plethora of assumptions, issues and uncertainties. As a general trend in all four countries, we observe a systematic underestimation with the average UA nearly two times greater than the average PA. Although the seagrass PAs and UAs indicate that nearly all of the classified seagrasses are also seagrasses in 'reality,' based on the validation data, our mapping does not capture more than half of the validated seagrasses across East Africa (average PA of 45.1%). Two main parameters may come into play here. Figure 2 unveils that the training data cover Rrs reflectance values consistently lower than the ones covered by the validation data which might have induced misclassifications of seagrasses as brighter yet similarly looking coral/algae and microalgal mats. This is a typical issue in machine learning which does not generalize well outside of the range of the training data. The differences

Table 3. Minima-maxima of in situ seagrass carbon stock estimates in East Africa.

Scale	Carbon Stock min (Mg/km^2)	Carbon Stock max (Mg/km^2)	Source
East Africa	*1000*	*82 900*	Howard et al. (2014)
Kenya	11 765.25	43 045.85	Githaiga et al. (2017), Kamermans et al. (2002), Juma et al. (2020)
Tanzania	571.19	6233.50	Belshe et al. (2018), Gullström et al. (2021), Lyimo et al. (2006), Lyimo et al. (2008)
Mozambique	922.89	2447.11	Bandeira (1997), de Boer (2000), Green and Short (2003), Gullström et al. (2021)
Madagascar	922.89	2447.11	Bandeira (1997), de Boer (2000), Green and Short (2003), Gullström et al. (2021)
East Africa	3545.56	13 543.39	Same sources as the country-scale estimates

Estimates are given for both region-specific Tier 1 (*in italics*) and country-specific Tier 2 assessments. Tier 1 carbon stocks represent soil organic carbon within the first meter of depth, while Tier 2 ones represent total carbon stocks in the living biomass (above- and below-ground) and seagrass soil. Mg denotes Megagrams, a unit of mass equal to 1 metric ton. The final regional estimate is averaged from the four country-specific ranges, is given only for reference and has not been used in any assessment.

in the spectral ranges covered by the training and validation data points may have been also introduced by our multi-temporal analytics: these reduced all integrated 16 453 Sentinel-2 tiles to the lowest (darkest) 20% of their reflectances across the temporally aggregated composite. Such low values practically represent the highest seagrass (dark pixels) density per pixel. The second potential source of underestimation might arise from the difference in spatial resolution between Sentinel-2, with a single pixel covering 100 m^2, and the various high-resolution field data collections which might have introduced mixed pixels.

To reduce such underestimations and other uncertainties in spatially explicit coastal ecosystem extent assessments in the future, analysts may conduct a more effective reference data design which, without being an exhaustive list of recommendations, could feature:

aTraining and validation data points that come from independent sources of different spatial resolution (higher one for the validation data) to reduce spatial autocorrelation bias, yet temporally close to ensure no additive bias due to possible habitat changes in the period between the different data collections (Finegold et al., 2016).

bImage annotation carried out by experienced individuals with the targeted geographical area and the studied benthic habitats. This will ensure that each annotated benthic habitat on the satellite basemap is truly existent at the very same location.

cHarmonized ranges, medians and means of the training and validation data to aid the generalization of the designed machine learning approaches.

dA depth stratification of the benthic habitat reference data using bathymetry data ideally at the same spatial resolution across equal intervals (e.g. every 1, 2, 5 m) to allow an equal and representative sample size for all the benthic classes (Finegold et al., 2016).

The value of every single remote sensing assessment is further enhanced when compared with existing estimates across similar spatial scales. Our remotely sensed physical accounts can be quantitatively compared with only a handful of existing mapping products across and within East Africa. Harcourt et al. (2018) calculated the countrywide seagrass extent of Kenya at 308.4 km^2 using also Sentinel-2 satellite images from 2016, 371.2 km^2 lower than our mapped seagrass extent. And UNEP-WCMC and Short (2018) yielded a Kenya-wide seagrass extent of 113.2 km^2, approximately six times smaller than our Kenyan estimate. Furthermore, according to UNEP-WCMC and Short (2018) and National Geographic Society (2000) (only for Madagascar), the seagrasses in Tanzania, Mozambique and Madagascar cover an extent of 46.1, 728 and 5793.5 km^2, respectively. While this means that the best available seagrass extent for Tanzania and Mozambique may be underestimated by one order of magnitude and by more than 1000 km^2, correspondingly, the Madagascan seagrasses may be overestimated more than fourfold. The observed differences between our national inventories and the aforementioned ones corroborate the observed and discussed biases elsewhere (Traganos, Aggarwal, et al., 2018). These biases could be attributed to the fact that these studies do not feature spatially explicit and comprehensive estimations as they are based on interpolated knowledge from multiple experts, data sources and decades, unlike our spatially explicit estimates based on a single, seamless and standardized big satellite dataset of more than 1.2 billion pre-processed pixels.

National seagrass carbon stocks in East Africa

The 100-fold difference between our calculated Tier 1 minimum and maximum seagrass carbon stock, although

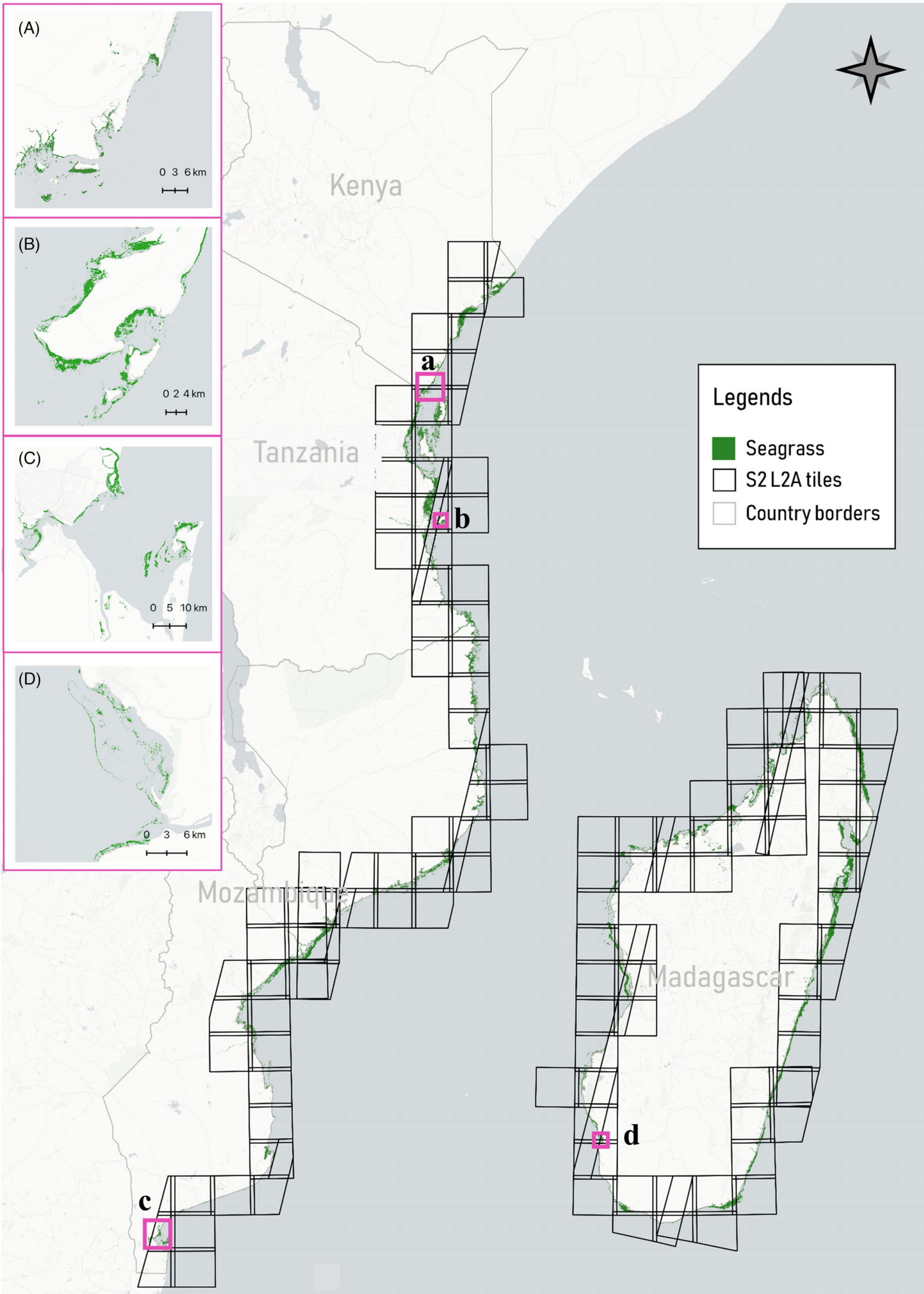
(A)
0 3 6 km
(B)
0 2 4 km
(C)
0 5 10 km
(D)
0 3 6 km
Kenya
Tanzania
Mozambique
Madagascar
a
b
c
d
Legends
Seagrass
S2 L2A tiles
Country borders

Figure 4. The nationwide extents of seagrass ecosystems in East Africa. The four pink inset panels show local-scale seagrass extents in each of the four mapped countries: (A) Kwale County coast province, Kenya; (B) Mafia, Juani and Jibondo Islands, Tanzania; (C) Maputo Bay, Mozambique; (D) Coastal waters of Toliara town, Madagascar. The S2 L2A tiles are Sentinel-2 surface reflectance data—16 453 cloud-free tiles (100 × 100-km) were used in our multinational ecosystem accounting.

Table 4. Estimated ranges of national and regional seagrass carbon stocks in East Africa.

	Tier 1 assessment		Tier 2 assessment	
Scale	Carbon stock min (Mg)	Carbon stock max (Mg)	Carbon stock min (Mg)	Carbon stock max (Mg)
Kenya	679 590	56 338 011	7 995 546	29 253 529
Tanzania	548 160	45 442 464	313 104	3 416 955
Mozambique	1 779 300	147 503 970	1 642 089	4 354 146
Madagascar	1 309 340	108 544 286	1 208 370	3 204 101
East Africa	**4 316 390**	**357 828 731**	**11 159 109**	**40 228 732**

Bold values are the regional sum of all columns.
These are based on Tier 1 and Tier 2 assessments (Kennedy et al., 2014), and in situ carbon stock data from Table 3 (for the Tier 2 assessment). Tier 1 carbon stocks represent soil organic carbon within the first meter of depth, while Tier 2 ones represent total carbon stocks in the living biomass (above- and below-ground) and seagrass soil. Mg denotes Megagrams, a unit of mass equal to 1 metric ton.

reduced to a 10-fold difference between minimum and maximum carbon stock in our Tier 2 assessment, reflects the large uncertainties and biases in attempting to calculate country or site-specific carbon stocks in seagrasses using globally averaged values; highlights the poor representation of East African seagrasses, and more broadly, the carbon-dense tropical Indo-Pacific seagrass bioregion in global datasets; and invokes prudent scientific efforts to pair Earth Observation advances and frameworks, like the one developed here, with existing and new field-collected seagrass carbon stocks to unveil and understand carbon storage and sequestration of seagrasses in similar data-poor seagrass bioregions. A further comparison to the only other existing national seagrass carbon estimate across East Africa by Harcourt et al. (2018)—7.65 million Mg of carbon stored in the Kenyan seagrasses—reveals that the latter estimate falls closer to the minimum of our Tier 2 calculation, owing probably to their more than twofold lower seagrass extent.

Earth Observation and ecosystem accounting: a contemporary synergy for blue carbon policy uptake and financing

The integration of Earth Observation advances into Ecosystem Accounting can be a promising systems-level approach to mainstream blue carbon ecosystems and their holistic natural climate solutions to biodiversity, societies and economies. Through this systems approach, harmonized geospatial and biophysical accounts reliant on ecological knowledge, translated into economic units (i.e. commodities) and measurable targets, and organized thematically around environmental policies (thematic accounting) can supercharge holistic insights and actions in the blue carbon realm (United Nations, 2021). This holistic accounting could essentially synthesize large-scale stacks of blue carbon co-benefits with associated uncertainties, allowing in turn equally blended forms of finances for conservation and restoration (Macreadie et al., 2021; Siman et al., 2021; United Nations Environment Programme, 2020a).

In the present study, we designed, developed and applied a cloud-native ecosystem accounting prototype to convert over three trillion and 26 terabytes of atmospherically corrected Sentinel-2 pixels into consistent nationwide accounts of seagrass extent and carbon stocks in Kenya, Tanzania, Mozambique and Madagascar. Our framework is enabled by the unprecedented parallel processing of the Google Earth Engine cloud architecture, open, dense time series of high-resolution optical satellite images, and existing regional reference data collations—a contemporary trifecta that can allow comprehensive, standardized spatial seagrass accounts, as demonstrated for East Africa here. Our prototype can be scaled to cover existing large spatial gaps in national seagrass extents and constrain uncertainties in seagrass ecosystem condition, services and monetary accounts—especially in global hot spots of blue carbon, coastal biodiversity and areal loss like the tropical Indo-Pacific, tropical Atlantic and Mediterranean bioregions (de los Santos et al., 2019; Dunic et al., 2021; Siman et al., 2021). Countries who have included seagrasses and coastal ecosystems in their current NDCs can be particularly benefited from our approach to both update their national GHG inventories

and put forward measurable targets for their conservation, following the examples of the Bahamas and Seychelles (Climate Change and Energy Department, 2021; United Nations Environment Programme, 2020a). Following the aforementioned uncertainties in sections 4.1 and 4.2, and the conceptualized systems-level approach here, potential future large-scale coastal accounting efforts aiming policy uptake may explore:
aSpatial harmonization and amalgamation of existing big reference data on benthic ecosystem extent (Borrego-Acevedo et al., 2020; Roelfsema et al., 2021) with large-scale automated training data annotations using machine learning and big spaceborne lidar data like ICESat-2 (Thomas et al., 2021)
bDevelopment and integration of spatially explicit validation metrics (e.g. confidence, uncertainty) which allows a better understanding and reduction of the biases in the approach and data. In addition, this is also a more effective communication and production of policy-relevant monetary accounts
cMaterialization of scalable proof of concepts via verified methodologies (Emmer et al., 2021) to create carbon stock and flux inventories based on seagrass meadows. This will contribute to the blue carbon crediting schemes and may also allow uptake of these fluxes in the Environmental, Social and Governance (ESG) goals of large companies which require such data to showcase sustainable supply chains in order to grow and attract investors

Technological advancements of our presented coastal ecosystem accounting framework and effective collaboration with relevant stakeholders can lay the foundations of a large-scale decision support system for coastal resilience in the 21st century and beyond. This is the ultimate aim of the Global Seagrass Watch project of the German Aerospace Center through which we are evolving the technology and products of this study.

Acknowledgments

The authors acknowledge WWF for funding and supporting this study through the Oceans Practice Innovation fund. DT and APP acknowledge Deutsches Zentrum für Luft- und Raumfahrt for funding and support through the Global Seagrass Watch project. CBL acknowledges support from a DLR-DAAD Research Fellowship (No. 57478193). DT, APP and CBL also acknowledge EO Data Science and Yvonne Fong for all the provided technical support through the Group on Earth Observations (GEO) and Google Earth Engine program. Last but not least, the authors acknowledge the Reef Check Foundation, the Allen Coral Atlas project and especially the Remote Sensing Research Centre team in the University of Queensland for the kind and invaluable provision of their benthic reference data collations.

Data accessibility

We provide the regional Sentinel-2 percentile composite at 10-m resolution, all of our remotely sensed regional mapping data (seagrass extent, satellite-derived bathymetry and turbidity), and our transformed seagrass and non-seagrass reference data in an interactive Google Earth Engine app (https://aviputri.users.earthengine.app/view/mappingeastafrica). All the displayed datasets can be also provided as rasters and/or shapefiles from the corresponding author on reasonable request through e-mail. Due to the commercialization aim of our DLR-funded Global Seagrass Watch project, we cannot provide access to the developed cloud-native ecosystem accounting algorithms. The Sentinel-2 image archive used for this analysis is available from the European Union Copernicus Open Access Hub (scihub.copernicus.eu), and through the Google Earth Engine data archive (http://earthengine.google.com).

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Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Table S1. Depth ranges and associated ratios of utilized training to validation data.
Figure S1. Local-scale distribution of training data points across East Africa.
Table S2. Error matrices of classified national seagrass and non-seagrass extents in East Africa.
Table S3. Statistics of out utilized multilinear SDB regression method across all tested band combinations of Sentinel-2 in East Africa. R
Table S4. Error matrix of regional turbidity detection in East Africa

