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Assessing the Carbon Sequestration Potential of Human-Controlled Wetlands: A Remote Sensing Approach Using Google Earth Engine

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Abstract: Blue carbon ecosystems, including mangroves, seagrasses, and salt marshes, play a crucial role in mitigating climate change by capturing and storing atmospheric CO_2 at rates exceeding those of terrestrial forests. This study explores the potential of HCWs (Human-Controlled Wetlands) in the Italian Venice Lagoon as an underappreciated component of the global blue carbon pool. Using GEE (Google Earth Engine), we conducted a large-scale assessment of carbon sequestration in these wetlands, demonstrating its advantages over traditional in situ methods in addressing spatial variability. Our findings highlight the significance of below-water mud sediments as primary carbon reservoirs, with a TC (Total Carbon) content of 3.81% ±0.94% and a stable storage function akin to peat, reinforced by high CEC (Cation Exchange Capacity). GEE analysis identified a redoximorphic zone at a depth of 20-30 cm, where microbial respiration shifts to anaerobic pathways, preventing carbon release and maintaining long-term sequestration. The study also evaluates key factors affecting remote sensing accuracy, including tidal variations, water depth, and sky cover. The strong correlation between field-measured and satellite-derived carbon parameters ($R^2 > 0.85$) confirms the reliability of our approach. Furthermore, we developed a GEE-based script for monitoring sediment bioturbation, leveraging Sentinel-1 SAR (Synthetic Aperture Radar) and Sentinel-2 optical data to quantify biological disturbances affecting carbon fluxes. Our results underscore the value of HCWs for carbon sequestration, reinforcing the need for targeted conservation strategies. The scalability and efficiency of remote sensing methodologies, particularly GEE, make them essential for the long-term monitoring of blue carbon ecosystems and the development of effective climate mitigation policies.

Key words: Blue carbon, HCWs, GEE, carbon sequestration, remote sensing, bioturbation, redoximorphic zone, carbon flux.

1. Introduction

Blue carbon, the carbon sequestered and stored in coastal and marine ecosystems, plays a critical role in mitigating global climate change. Temperate wetlands, including salt marshes, seagrass meadows, and mangroves, recognized vital reservoirs of blue carbon due to their capacity to capture and store carbon for extended periods. HCWs (Human-Controlled Wetlands), such as constructed wetlands, are increasingly gaining attention for their potential contribution to blue carbon sequestration. Despite their importance, assessing blue carbon sinks in these ecosystems remains a complex and time-intensive process, often requiring field-based measurements, sophisticated models, and multidisciplinary datasets. Advances in remote sensing technologies and platforms like GEE (Google Earth Engine) have revolutionized environmental monitoring by offering scalable, cost-effective tools for analyzing ecosystems. Since its public release in 2010, GEE has provided researchers and practitioners with access to an extensive archive of geospatial data, combined with powerful cloud-based computational capabilities. This platform enables rapid analysis of critical ecosystem parameters, making it a game-changer for environmental science. However, there is a need for tailored tools and scripts to simplify the quantification of blue carbon potential

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in wetlands, especially for checks and decision-making processes. Furthermore, ensuring reproducibility and accuracy of results requires the inclusion of the date of run, as geospatial data in GEE can change over time due to updates in datasets or changes in ecosystem conditions. The goal of this study is to develop a robust GEE script designed to automate the rapid assessment of ecosystem parameters relevant to blue carbon sink evaluation in temperate and HCWs. The script includes functionality to document the date of execution to ensure state-specific results and transparency. This tool aims to streamline the carbon credit pre-certification process by enabling scientists to efficiently analyze vegetation cover, soil carbon, hydrological dynamics, and other key indicators. This paper outlines the development, functionality, and potential applications of the script.

2. Methods

This study was conducted in the Venetian Lagoon, Italy, a temperate wetland ecosystem characterized by complex interactions between ecological and anthropogenic factors. Within this system, Val Dogà (45.558261 °N, 12.536424 °E) was selected for its high carbon sequestration capacity [1]. These historical wetlands are engineered systems designed to optimize carbon retention through hydrological control, biomass preservation, and sediment management. Functionally analogous to temperate peatlands, these HCWs sustain long-term carbon storage by maintaining anaerobic, waterlogged conditions that limit microbial decomposition [2]. HCWs exhibit a fossorial carbon system, a stable belowground carbon reservoir composed of organic-rich sediments. These sediments include mud deposits enriched with DOC (Dissolved Organic Carbon) and particulate organic matter from algae, submerged vegetation, and detritus. Their high CEC (Cation Exchange Capacity) enhances long-term carbon retention [3]. Unlike unmanaged wetlands, the controlled hydrology of HCW minimizes carbon release by preventing drainage and sustaining anaerobic conditions [4]. Below-water mud sediments in HCW were found to contain TC (Total Carbon) at 8.56% ± 0.94%. The carbon pool is further enriched by contributions from decaying seagrasses, halophytic plants, and algae, forming a dynamic reservoir of organic matter. To quantify and validate carbon sequestration processes, multi-sensor satellite data from the GEE platform were utilized. Remote sensing approaches enabled systematic assessment of five primary carbon pools:

(1) AGB (Above-Ground Biomass) of Halophytes

Dominated by Tamarix sp., which contributes significantly to carbon storage.

Tamarix sp. exhibited an average TC content of 48.42% dw.

Functions as an alternative to mangroves in temperate regions.

(2) Algae and Seagrass Biomass

Key species include *Ruppia maritima* (30.95% dw TC) and *Cymodocea nodosa* (27.54% dw TC).

Macroalgae, such as *Chaetomorpha linum*, had a mean carbon content of 33.65% ± 7.99% [5].

(3) Below-Water Mud Sediments

The primary fossorial carbon baseline, enriched with decayed aquatic vegetation and seasonal biomass deposits.

(4) Above-Water Salt Marsh

Characterized by variable TC content (2%-11% dw), influenced by CEC and hydrological conditions.

(5) Carbon Fluxes and Productivity Estimations

Sentinel-2 spectral data facilitated the computation of GPP (Gross Primary Productivity), NEE (Net Ecosystem Exchange), and CO_2 fluxes using vegetation indices NDVI [6].

$$NDVI = (B8 - B4) / (B8 + B4)$$

Water areas utilized NDWI (Normalized Difference Water Index) [7] to analyse hydrological conditions.

2.1 Water Quality and Biogeochemical Indicators

Satellite-based analyses integrated empirical models for key aquatic indicators: Chlorophyll-a (Chl_a) [8];

Cyanobacteria (Cya) [9]; Turbidity (Turb) [10]; CDOM (Chromophoric Dissolved Organic Matter); DOC (Dissolved Organic Carbon) [11].

2.2 Atmospheric Carbon Monitoring

To estimate atmospheric CO_2 levels, the COPERNICUS/S5P/NRTI/L3_CO dataset was employed. Since CO (Carbon Monoxide) acts as a proxy for CO_2, conversion was applied following Kaiser et al. [12]:

$$\text{CO to CO}_2 \text{ equivalent} = \text{CO (ppm)} \times 10{,}000$$

Adjustment factor of 1.15 is applied for in situ validation.

To enhance accuracy, an APA Script (Aquatic Plants and Algae Custom Script Detector) was integrated into GEE [13], automating aquatic vegetation classification and field site selection. This automation improved spatial accuracy and reduced manual effort. Beyond Sentinel-2, the study incorporated:

(1) MODIS/061/MOD11A1 LST

Used for estimating soil and water temperature, influencing respiration rates [14].

Respiration was modeled using the Q10 temperature dependence equation: Respiration = Rbase * Q10 * ((Temp - 10) / 10);

[14], where Rbase = 0.5, Q10 = 2.0.

(2) Dynamic World (GOOGLE/DYNAMICWORLD/V1)

Used for land cover classification, including intertidal zones, marshes, and submerged vegetation [15].

(3) SRTM (Shuttle Radar Topography Mission) Elevation (USGS/SRTMGL1_003)

Assessed topographic variation, influencing water retention, sediment deposition, and vegetation distribution [16].

(4) Soil Data (OpenLandMap)

Integrated bulk density and organic carbon datasets to estimate soil carbon stocks [17].

(5) Global Intertidal Classification (UQ/murray/Intertidal/v1_1/global_intertidal)

Identified intertidal zones crucial for carbon cycling [18].

(6) Globathy Bathymetry

Provided insights into underwater topography, crucial for sediment distribution [19].

(7) ETH (Swiss Federal Institute of Technology ETH Zurich) Global Canopy Height 2020 and GEDI ((Global Ecosystem Dynamics Investigation by NASA) Data Used for estimating above-ground biomass via vegetation height measurements [20, 21].

All remote sensing data were validated through field measurements and AI-driven models to ensure accuracy [22]. The integration of Sentinel-2's high-resolution spatial data with MODIS's frequent temporal coverage provided comprehensive monitoring of blue carbon sequestration in HCW. This multi-source approach strengthens the robustness of wetland carbon assessments and advances the accuracy of global blue carbon accounting frameworks.

3. Results

The analysis of blue carbon ecosystems is essential for understanding global carbon dynamics and mitigating climate change. These ecosystems—including wetlands, mangroves, seagrasses, and tidal marshes—act as significant carbon sinks by capturing and storing atmospheric CO_2. While natural blue carbon habitats have been extensively studied, our research highlights the underexplored potential of temperate, HCWs as a crucial component of the global blue carbon pool. Unlike natural wetlands, human-modified wetlands exhibit distinct carbon storage capacities, with carbon distributed across different pools compared to seagrasses and mangroves [23]. A comprehensive methodological approach is required to assess their carbon sequestration potential accurately. We applied three distinct approaches:

(1) In situ analysis (Fig. 1)

(2) An AI-driven approach (Fig. 2) and

(3) GEE-based satellite data integration (https://code.earthengine.google.com/76508751e945b8e450dee4a4637b5f4d) (Fig. 3).

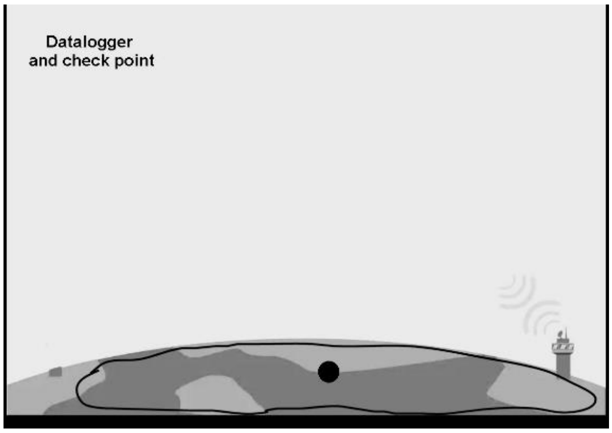

Fig. 1 Carbon sink ecosystem control by one point in situ analysis and a continuous datalogger.

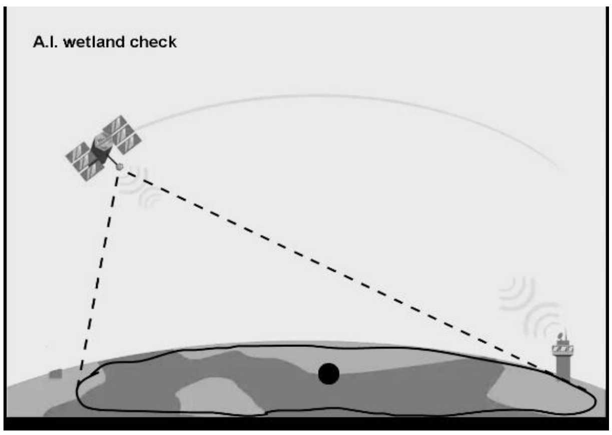

Fig. 2 Carbon sink ecosystem control using a combined AI system (data from analysis plus datalogger and satellite).

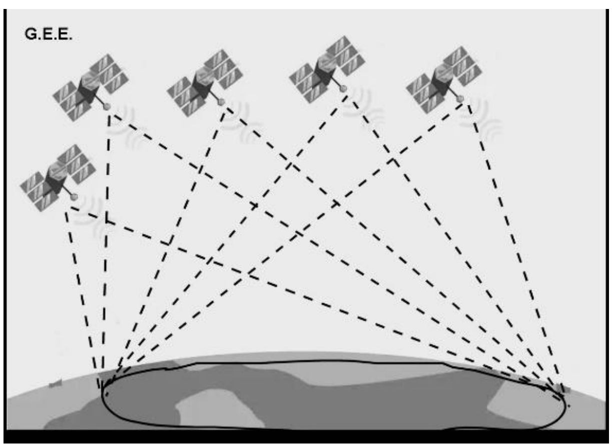

Fig. 3 Carbon sink ecosystem control using a multiple satellite database GEE.

A comparative analysis of these methods is presented in Table 1, while the mean carbon accumulation rate is shown in Table 2. Our findings indicate that restoration and improved management of HCWs could significantly enhance their role as carbon sinks [24, 25]. For further discussion on HCWs, refer to Doimi's video YouTube Link (https://youtu.be/81z23IfAlTY) [26, 27].

The evaluation of wetland carbon sequestration rates was conducted using three distinct methodologies: GEE, in situ analysis, and an AI (Artificial Intelligence)-based approach. The results, expressed in grams of carbon per square meter per day (g/cm^2/day), demonstrate variations in carbon sink rates across different wetland zones and biomass categories. The total WCS rate showed significant discrepancies between the methods. The AI-based approach estimated the highest TC sink rate (8.47 g/cm^2/day), more than double the values obtained from both GEE (3.56 g/cm^2/day) and in situ analysis (3.68 g/cm^2/day). This suggests that the AI model might be capturing additional carbon storage dynamics, particularly within the water wetland zone, which exhibited the most substantial difference (8.07 g/cm^2/day in AI vs. 2.08 g/cm^2/day in GEE and 2.9 g/cm^2/day in in situ analysis). In the land wetland zone, GEE estimated the highest carbon sink rate (1.48 g/cm^2/day), nearly double that of in situ analysis (0.78 g/cm^2/day) and almost four times the AI-derived estimate (0.39 g/cm^2/day). This suggests that satellite-based remote sensing methods may capture a broader range of carbon fluxes in land zones, while AI techniques might be more conservative in estimating terrestrial carbon sequestration. For above-ground biomass, both tree and non-tree carbon sink rates varied notably among methods. In situ measurements yielded the highest values for both above-ground tree (0.37 g/cm^2/day) and non-tree (0.40 g/cm^2/day) carbon sink rates, indicating the potential for underestimation in remote sensing and AI-based approaches. GEE and AI estimates for tree carbon sink rates were relatively similar (0.20 and 0.29 g/cm^2/day, respectively), but AI significantly underestimated the non-tree carbon sink rate (0.09 g/cm^2/day) compared to both in situ (0.40 g/cm^2/day) and GEE (0.26 g/cm^2/day). These findings highlight key methodological differences in carbon sequestration assessments. While in situ analysis

Table 1 Comparative analysis of methods to evaluate HCW carbon sink activity. Lat. 45.56070 N; long. 12.52913 E.

Parameter	GEE	In situ analysis (*)	AI
Area of selected place (ha)	1,309.382766	1,309.382766	1,309.382766
Data of beginning	15/07/2024	15/07/2024	15/07/2024
Data of end	17/07/2024	17/07/2024	17/07/2024
Mean temp. in the region (℃)	33.90380488	26	26
Mean SHR (Wetland Heterotrophic Respiration) (g/cm^2/day)	2.528846019	2.9	-
Mean GPP (g/cm^2/day)	34.84163932	45	-
Mean Net CO_2 (g/cm^2/day)	-1.482872963	-2	-
Mean Chl_a (Chlorophyll-a)	7.731967475	9.7	-
Mean PAR	70	53.1	-
Mean Cya (Cyanobacteria)	5.52E+12	-	-
Mean turbidity (NTU)	3.86981434	5.86	-
Mean CDOM	23.74547792	-	-
Mean DOC	39.73943702	-	-
Mean color	206.0762702	-	-
Mean CO_2 (ppm)	390	400	-
Mean water CO_2 (ppm)	1,129	207.74	-
Total algae area (m^2)	3,773,786.59	6,209,705.76	-
Total water area (m^2)	9,641,349.438	8,757,700.00	-
Min water deep (mt)	1.04	-	-
Max water deep (mt)	6.84	-	-
Mean water deep (mt)	4.92	0.5	-
Trees area (ha)	9.055336145		-
Grass area (ha)	0		-
Flooded_vegetation area (ha)	115.0267198	858.3900	-
Crops area (ha)	0.540515129		-
Shrub_and_scrub area (ha)	0		-
Intertidal area (ha)	947.8462		-
Stat. Elevation (SRTM) min mt.	-9	-	-
Stat. Elevation (SRTM) max mt.	8	-	-
Stat. Elevation (SRTM) mean mt.	-0.2	-	-
FAI (Floating Algae Index)	281	417	
NDWI	-0.004044	-	
DBH	13.56	16.68	
Tamarix tree number	227,689	220,282	
Canopy height Lang 2022 98%	10.33	-	-
Canopy height Potapov 2021 95%	0.06	-	-
Canopy height (≥ 1 m)	4.06	5	4
Canopy height (m)	0.035	-	-
Soil density Min (×10 kg/m^3)	100	138	-
Soil density Max (×10 kg/m^3)	140	146	-
Soil density Mean (×10 kg/m^3)	126	-	-
Mean soil organic carbon (0 cm deep)	3.82	-	-
Mean soil organic carbon (10 cm deep)	3.81	-	-
Mean soil organic carbon (30 cm deep)	1.98	2.52	-
Mean soil organic carbon (60 cm deep)	1.21	-	-
Mean soil organic carbon (100 cm deep)	1.13	-	-
Mean soil organic carbon (200 cm deep)	0.87	-	-

*: R^2 values exceeding 0.85.

Table 2 Mean carbon accumulation rate on HCW, lat. 45.56070 N; long. 12.52913 E.

Parameter	GEE ($g/cm^2/day$)	In situ analysis (*) ($g/cm^2/day$)	AI ($g/cm^2/day$)
Wetland area (ha)	1,309.38	1,309.38	1,309.38
Above Ground Tree Carbon Sink rate	0.20	0.37	0.29
Above Ground not Tree Carbon Sink rate	0.26	0.40	0.09
Land Wetland zone Carbon Sink rate	1.48	0.78	0.39
Water Wetland zone Carbon Sink rate	2.08	2.9	8.07
Tot WCS (Wetland Carbon Sink) rate	3.56	3.68	8.47

*: R^2 values exceeding 0.85.

provides direct field-based measurements, GEE offers large-scale, consistent monitoring capabilities, and A.I. models may capture complex interactions but require further validation. The discrepancies underscore the need for hybrid approaches that integrate the strengths of each method to improve the accuracy and scalability of WCS assessments. Furthermore, the integration of high-resolution datasets and customized algorithms provides robust insights into ecological patterns and processes that would be difficult to discern through traditional methods. The below-water mud sediments in HCWs exhibited a TC content of 3.81% ± 0.94%, serving as the primary reservoir for FMA (Fossorial Mud Activity) carbon storage. These sediments, enriched with organic matter from decaying aquatic vegetation and fauna, function as stable carbon sinks, similar to peat. This stability is reinforced by the high CEC of the soils, which prevents carbon release under waterlogged conditions. GEE analysis confirmed our hypothesis regarding the redoximorphic zone, identifying it at a depth of 20-30 cm, where significant shifts in carbon concentrations occur (Fig. 4). This zone forms below the surface layer in oxygen-limited conditions, where microbial activity transitions from aerobic to anaerobic processes. As oxygen is depleted, microbes utilize alternative electron acceptors such as nitrate, sulphate, or carbon dioxide for respiration, ultimately leading to methane formation.

The correlation (Fig. 5) between HET (Wetland Heterotrophic Respiration) and WCS can provide valuable insights into carbon cycling in wetland ecosystems. A visual inspection of the data suggests a positive relationship between HET and WCS, indicating that as heterotrophic respiration increases, the carbon sink capacity of wetlands also tends to rise. This trend aligns with ecological expectations, where higher microbial respiration rates correspond to increased carbon flux. The Pearson correlation coefficient between HET and WCS is approximately 0.842, with a *p*-value of 1.18×10^{-5}. This indicates a strong positive correlation between the two variables, meaning that as heterotrophic respiration increases, the wetland's carbon sink capacity also tends to rise. The very low *p*-value suggests that this correlation is statistically significant, meaning the relationship is unlikely to be due to random chance.

It would suggest that wetland respiration plays a significant role in determining carbon sequestration levels. The GEE data scatter plot, shows in Fig. 6, a clear linear trend, meaning that as Net CO_2 increases, Land Carbon Sink also tends to increase. This suggests that the Land Carbon Sink is strongly linked to Net CO_2 emissions, which could have implications for carbon cycle modelling and climate studies.

3.1 GEE Sentinel Sat. for GPP and NEE Estimations

The application of satellite data from Sentinel-2 allowed for the estimation of GPP (Gross Primary Productivity), NEE (Net Ecosystem Exchange), and CO_2 fluxes in the study area. Vegetation indices, such as the NDVI and NDWI (Normalized Difference Water Index), were used to proxy photosynthetic activity, with GPP calculated based on the B8 (near-infrared) band. Maximum GPP was observed during the summer months, corresponding with peak photosynthetic activity, and was significantly influenced by temperature-

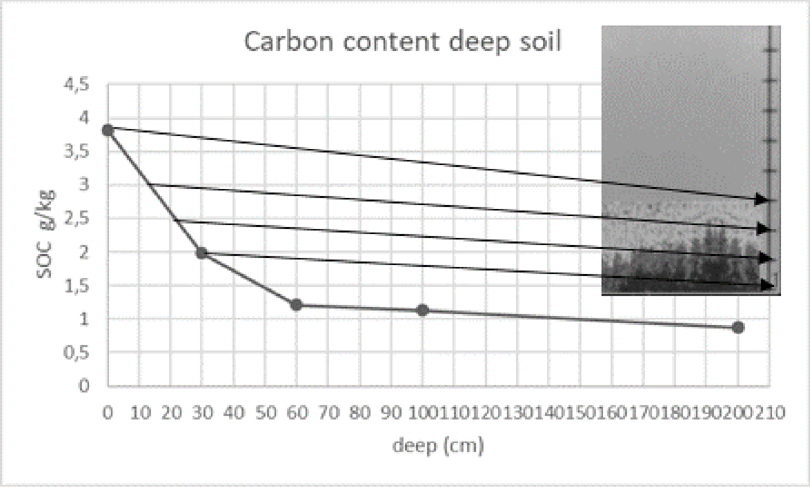

Fig. 4 GEE data result of deep soil carbon change content and sonar stratigraphic analysis of the HCW mud.

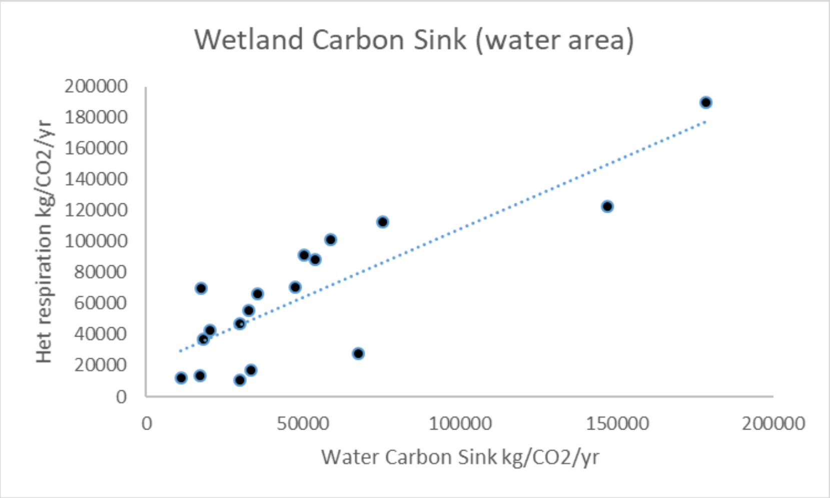

Fig. 5 The scatter plot showing the correlation between HET and WCS. The blue points represent the data values, while the blue dashed line is the trend line indicating the positive correlation. Pearson correlation coefficient is 0.842.

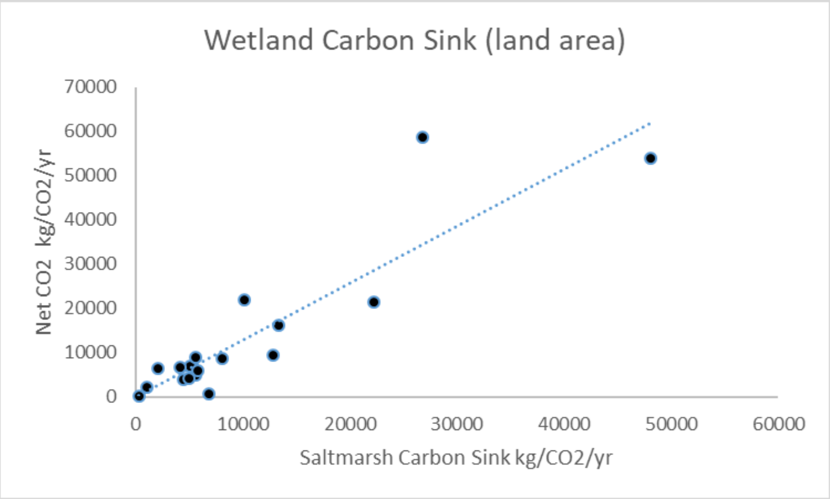

Fig. 6 Pearson correlation coefficient is 0.90, indicating a strong positive correlation between Net CO_2 and Land Carbon Sink. The *p*-value is very low (≈ 0.0000), confirming that the correlation is statistically significant.

dependent respiration rates, which were modelled using MODIS LST (Land Surface Temperature) data. NEE was calculated by subtracting respiration from GPP, revealing a net carbon sequestration during the growing season.

3.2 GEE Sentinel Sat. for Proxy CO_2 Analysis

The analysis of satellite-based carbon monoxide (CO) data, using a conversion factor between CO and CO_2, provided an estimate of CO_2 fluxes across the wetlands. The temporal and spatial correlation between CO and CO_2 emissions, especially from combustion sources, allowed for a reliable estimate of CO_2 fluxes using the Sentinel-2 data in conjunction with the AIRS (Atmospheric Infrared Sounder) and TROPOMI (Tropospheric Monitoring Instrument). This approach, based on the well-established relationship between CO and CO_2 in the atmosphere [28], confirmed the effectiveness of using satellite measurements to derive CO_2 estimates without extensive field sampling. The results revealed consistent CO_2 fluxes during the growing season, with variations based on local environmental conditions and anthropogenic influences.

4. Conclusion

Blue carbon ecosystems, including mangroves, seagrasses, and salt marshes, play a crucial role in mitigating climate change by capturing and storing atmospheric CO_2 at rates exceeding those of terrestrial forests. These ecosystems not only function as carbon sinks but also support biodiversity and protect coastal communities. The Blue Carbon Initiative, led by Conservation International, IUCN (International Union for Conservation of Nature), and IOC-UNESCO (Intergovernmental Oceanographic Commission of United Nations Educational, Scientific and Cultural Organization), aims to conserve and restore these habitats, contributing to global climate mitigation and sustainable livelihoods. Our study demonstrates that HCWs in the Italian Venice Lagoon represent a valuable and underexplored component of the global blue carbon pool. Their potential for carbon sequestration highlights the importance of conservation and restoration efforts to enhance atmospheric CO_2 removal. The integration of GEE has been pivotal in conducting large-scale assessments, providing a scalable and efficient method for monitoring blue carbon ecosystems worldwide.

Key factors influencing the accuracy of remote sensing analysis include:

(1) Water surface area, which fluctuates due to tidal variations [29, 30].

(2) Water depth, affecting the effectiveness of satellite-based observations [31, 32].

(3) Sky cover, which can limit remote sensing accuracy [33, 34].

Compared to traditional in situ measurements, GEE provides a significant advantage in addressing the spatial variability of wetland environments, where field analyses often lack representativeness. The high correlation ($R^2 > 0.85$) between remote sensing estimates and field-measured carbon parameters confirms the reliability of this approach. This validation underscores the feasibility of employing GEE for large-scale blue carbon assessments, particularly in remote and dynamic wetland regions [35, 36]. Wetland carbon sequestration involves both land-based and water-based carbon sinks, which contribute differently to overall carbon dynamics. The land-based sink includes Tamarisk plants, shrubs, and salt marsh soil, while the water-based sink consists of seagrass, algae, and sediment. These components interact through complex biological and geochemical processes [37], necessitating advanced remote sensing tools for accurate assessment. Using GEE, carbon sink estimations become more efficient and scalable, allowing for the integration of large datasets to quantify wetland carbon storage [38]. The TC sink can be now simplified approximated as:

$$\text{WCS} = \text{Heterotrophic Respiration} + \text{Net } CO_2$$

This equation provides a simplified yet comprehensive approach to assessing wetland carbon storage by incorporating key indicators of carbon sequestration (carbon sink pool) and release [37]. Our GEE analysis further highlights the critical role of below-water mud sediments in HCWs as primary carbon reservoirs, with a stable storage function similar to peat due to their high organic content and CEC [39]. The study confirms the presence of a redoximorphic zone at a depth of 20-30 cm, where carbon sequestration is most prominent. This anaerobic layer fosters microbial respiration using alternative electron acceptors, effectively preventing carbon release and maintaining the wetland's long-term carbon sink capacity [37]. Additionally, satellite-based datasets enable the detection of bioturbation activity, revealing the impact of biological disturbances on carbon fluxes [38]. Bioturbation, caused by sediment-dwelling organisms, influences sediment structure, stability, nutrient cycling, and geochemical processes [40]. To quantify this activity, we developed a GEE-based bioturbation monitoring script (Link) that integrates multi-sensor remote sensing data:

Sentinel-1 SAR imagery to assess surface roughness,

Sentinel-2 optical data to track NDVI and NDWI variations over time.

The result is shown in Fig. 7.

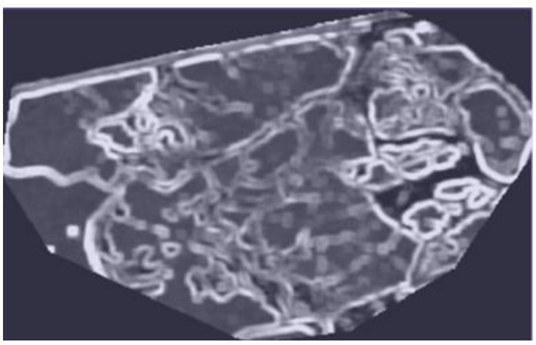

Fig. 7 Remote sensing approaches to visualize the selected area bioturbation (2023-2024). White: the max area of bioturbation.

While in situ measurements remain essential for validation—particularly for certification bodies—their reliability is often affected by environmental variability, sampling biases, and temporal inconsistencies [39]. Remote sensing approaches, therefore, offer a more standardized and comprehensive framework for assessing wetland carbon dynamics. These findings emphasize the importance of HCWs as effective carbon sinks, reinforcing the need for targeted conservation strategies and continued advancements in remote sensing methodologies to improve carbon sequestration monitoring on a global scale.

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