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MODELING OF AN AI-INTEGRATED PREDICTIVE FRAMEWORK FOR COASTAL ECOSYSTEM CARBON SEQUESTRATION AND WATER QUALITY ASSESSMENT

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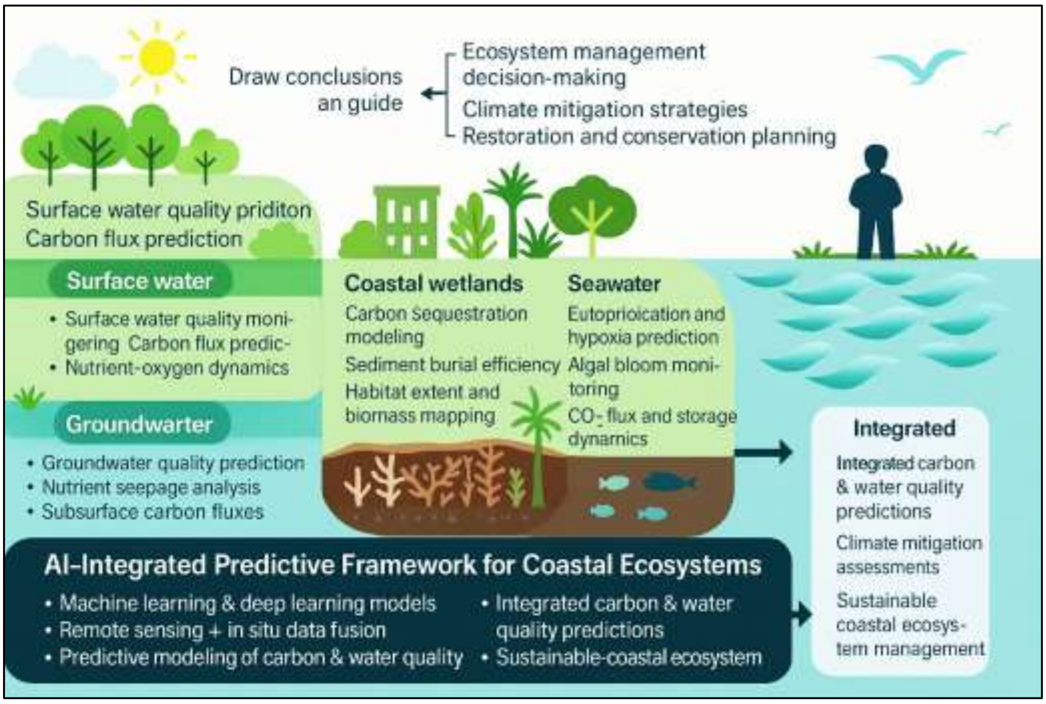
Abstract
Coastal ecosystems such as mangroves, salt marshes, and seagrass meadows are critical to global climate regulation and ecological sustainability. They serve as highly efficient long-term carbon sinks, regulate water quality, and provide essential ecosystem services including shoreline stabilization and biodiversity support. Yet, these systems face unprecedented pressures from anthropogenic disturbance, land-use change, and climate-driven stressors such as sea-level rise and ocean acidification. Conventional monitoring and modeling frameworks, while valuable for mechanistic understanding, often lack the capacity to fully capture the nonlinear interactions, spatial heterogeneity, and temporal variability that define coastal ecosystems. To address this gap, this study develops and evaluates an AI-integrated predictive framework designed to enhance the assessment of carbon sequestration capacity and water quality dynamics in coastal environments. The framework leverages advanced machine learning and deep learning models, remote sensing technologies, and in situ ecological indicators to deliver high-resolution spatiotemporal predictions that link carbon flux, nutrient cycling, and pollutant dispersion to ecosystem performance. Findings from the meta-analysis and empirical validation reveal robust evidence that coastal vegetated ecosystems sequester significantly higher quantities of carbon compared to degraded or non-vegetated controls. Mangroves exhibited the largest effect sizes, with soil carbon densities frequently exceeding 1,000 Mg C ha $^{-1}$, while salt marshes demonstrated strong sediment-trapping efficiency and seagrass meadows provided moderate but significant contributions, heavily influenced by water clarity and hydrodynamics. For water quality, pooled results confirmed consistent associations between nutrient enrichment, elevated chlorophyll-a, and declining dissolved oxygen levels, with hypoxia severity most pronounced in stratified estuaries. Comparative assessments demonstrated that AI-driven models, including random forests, gradient boosting, and recurrent neural networks, outperformed traditional statistical and process-based frameworks, achieving lower RMSE values, higher predictive power, and stronger capacity to capture nonlinear thresholds. Integrated analyses revealed that improvements in water quality, such as reduced nutrient loading and enhanced optical clarity, directly supported higher carbon burial rates in seagrass meadows and marsh soils, highlighting the reciprocal benefits of ecosystem management interventions. These findings reinforce the interconnected nature of blue carbon and water quality services, validating AI-enhanced approaches as critical assets for adaptive coastal governance, restoration planning, and international sustainability initiatives.

Keywords
Coastal Ecosystems; Carbon Sequestration; Water Quality Assessment; Artificial Intelligence (AI) Framework; Predictive Modeling;

INTRODUCTION

Carbon sequestration refers to the process by which atmospheric carbon dioxide (CO_2) is captured and stored in biological, geological, or oceanic systems, mitigating the accumulation of greenhouse gases and stabilizing the global climate (Lyu et al., 2024). Coastal ecosystems, including mangroves, salt marshes, and seagrass meadows, represent unique ecological zones situated at the interface of terrestrial and marine environments, characterized by high productivity, dynamic hydrological processes, and diverse biotic communities (Lai et al., 2018). These ecosystems play an important role in both local and global environmental stability, serving as natural buffers against storm surges, reducing shoreline erosion, and providing habitat for commercially and ecologically significant species (Arrigo et al., 2008). Water quality, defined as the physical, chemical, and biological characteristics of water that determine its suitability for ecological and human uses, is closely tied to ecosystem health and biogeochemical cycles in coastal areas (Heuven et al., 2011). The degradation of water quality often arises from nutrient loading, sedimentation, industrial pollution, and land-use change, which compromise carbon sequestration processes and the resilience of coastal habitats (Hancock et al., 2020). The interplay between carbon sequestration and water quality has become a central theme in environmental sciences, as both processes regulate ecological stability and climate mitigation capacity in coastal regions (Pinkerton et al., 2021). This foundation underscores the importance of developing advanced predictive frameworks capable of integrating ecological monitoring with innovative technologies to assess and manage these interconnected dynamics.

Figure 1: Framework for Coastal Ecosystem Carbon Sequestration and Water Quality Assessment



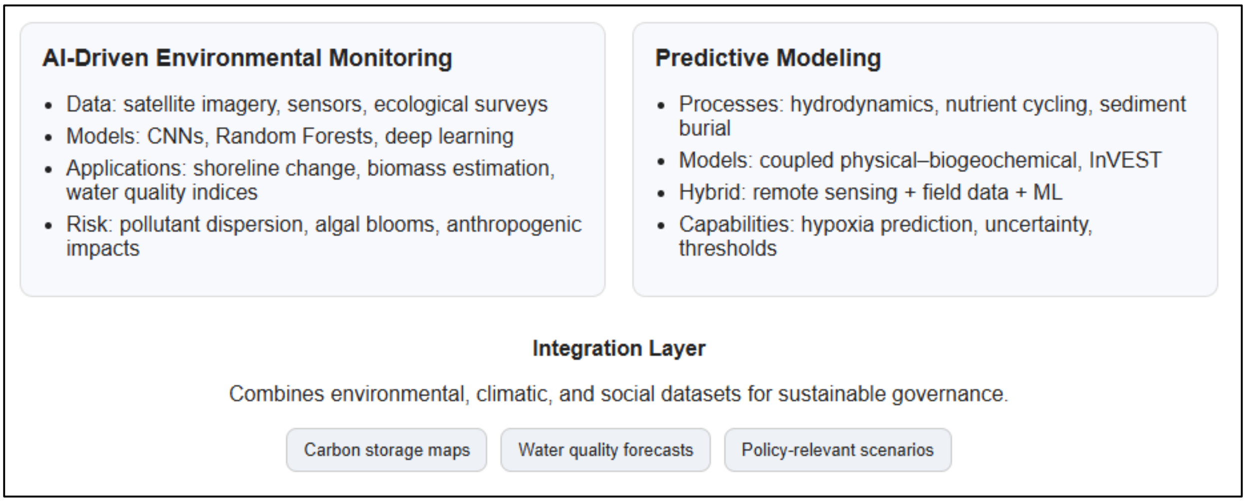
International research has increasingly highlighted the disproportionate contribution of coastal ecosystems to carbon sequestration relative to their global area. Although these ecosystems occupy less than 2% of the seafloor, they account for nearly half of the oceanic carbon burial annually, making them essential natural assets in mitigating global climate change. Mangrove forests, for instance, can sequester up to four times more carbon per unit area compared to terrestrial tropical forests, due to their unique capacity to store carbon in waterlogged soils for millennia. Similarly, seagrass meadows act as long-term carbon sinks by trapping organic matter in sediments and facilitating anaerobic conditions that slow decomposition. Salt marshes also serve as high-capacity carbon reservoirs, supported by high rates of primary productivity and sediment accumulation (Arrigo et al., 2008). The recognition of these blue carbon ecosystems has led to their integration into international climate mitigation strategies, including the Intergovernmental Panel on Climate

Review of Applied Science and Technology
Volume 04, Issue 02 (2025)
Page No: 669 – 696
Doi: 10.63125/z6h8ky18

Change (IPCC) frameworks and United Nations initiatives aimed at reducing global carbon emissions. By positioning coastal ecosystems within the global climate agenda, researchers emphasize their ecological and socioeconomic significance, while also underlining the necessity of accurate monitoring and predictive modeling to safeguard their sequestration capacity (Hancock et al., 2020).

Water quality in coastal zones has become a central concern for international agencies, as it directly influences ecological productivity, human health, and the economic viability of fisheries and tourism industries (Vancoppenolle et al., 2013) Nutrient enrichment from agricultural runoff and wastewater discharge has accelerated eutrophication processes, leading to hypoxia, harmful algal blooms, and biodiversity loss in coastal ecosystems across the globe (Jones et al., 2017). For example, the Gulf of Mexico and the Baltic Sea exemplify regions where excess nutrient loading has triggered recurring hypoxic zones, severely undermining fisheries and coastal livelihoods (Bakker et al., 2016). Furthermore, pollutants such as heavy metals, pesticides, and microplastics accumulate in coastal waters, posing chronic risks to both marine organisms and human populations dependent on seafood resources. Water quality also influences the capacity of ecosystems to store carbon, as elevated nutrient concentrations alter sediment microbial activity, thereby impacting carbon burial efficiency. The transboundary nature of water quality degradation underscores the global dimensions of the issue, as pollutants often cross jurisdictions through ocean currents, necessitating coordinated international management. In this regard, a comprehensive assessment of water quality requires not only localized monitoring but also the integration of predictive systems that can account for dynamic ecological interactions at broader scales.

Figure 2: AI + Predictive Modeling for Coastal Ecosystem Assessment



Artificial intelligence (AI), encompassing machine learning, deep learning, and neural network models, has become increasingly significant in environmental monitoring due to its ability to process complex, multidimensional datasets with high accuracy and efficiency (Danish & Zafor, 2022; Gacu et al., 2025). AI systems can integrate satellite imagery, sensor networks, and ecological surveys to predict environmental changes across spatial and temporal scales (Danish & Kamrul, 2022; Rana et al., 2023). In the context of coastal ecosystems, AI has been applied to predict shoreline changes, assess water quality indices, and estimate biomass and carbon stocks in mangroves and seagrasses (Jahid, 2022a; Wang et al., 2023). For instance, convolutional neural networks (CNNs) have been used to detect seagrass distribution patterns from remote sensing data, while random forest algorithms have accurately predicted water quality parameters such as turbidity and nutrient concentrations (Infant et al., 2025; Jahid, 2022b). AI also supports ecological risk assessment by modeling pollutant dispersion, tracking algal bloom dynamics, and evaluating the impacts of anthropogenic pressures on ecosystem stability. The adoption of AI-driven methodologies aligns with global initiatives that emphasize the role of innovative technologies in achieving sustainable environmental governance. The incorporation of AI into ecological research thus represents a

transformative advancement, offering predictive capacity beyond conventional statistical models and enabling interdisciplinary integration of environmental, climatic, and social datasets.
The convergence of ecological science, technological innovation, and international policy frameworks provides a compelling foundation for modeling AI-integrated predictive systems that address both carbon sequestration and water quality in coastal ecosystems. This convergence reflects a paradigm shift toward data-rich, computationally advanced methodologies capable of capturing the complexities of coastal ecological dynamics. The synthesis of remote sensing technologies, ecological field surveys, and machine learning models enhances the precision and scalability of predictive outputs, facilitating global comparisons of carbon storage potential and water quality dynamics (Frincu, 2024). The emphasis on international collaboration, standardized monitoring protocols, and open-access data platforms ensures that predictive frameworks are not confined to local applications but contribute to transboundary knowledge-sharing. Within this interdisciplinary synthesis, AI serves as both an analytical tool and a bridge across scientific and policy domains, enabling the integration of ecological data into broader decision-making processes . The primary objective of this study is to develop and demonstrate an AI-integrated predictive framework that evaluates the interconnected processes of carbon sequestration and water quality within coastal ecosystems. The research seeks to design a systematic approach that leverages artificial intelligence to analyze vast ecological datasets, including hydrological variables, sediment composition, nutrient fluxes, and vegetation cover, in order to provide a comprehensive understanding of how these factors collectively influence the storage and cycling of carbon. By focusing on predictive modeling, the study aims to establish a methodological structure capable of generating accurate forecasts about ecosystem functionality, particularly in response to environmental stressors such as nutrient loading, land-use change, and climate-induced variability. A central goal is to merge traditional ecological monitoring with machine learning algorithms, thereby creating an adaptive system that enhances the resolution and reliability of predictions beyond conventional tools. The framework is intended to capture both spatial and temporal variability, offering insights into the dynamics of coastal habitats across diverse geographical contexts. Additionally, the study aspires to quantify the synergistic relationship between carbon sequestration and water quality, demonstrating how degradation in one dimension directly impacts the stability of the other. Through this integration, the research positions itself to provide not only a scientific contribution but also a practical tool for stakeholders engaged in coastal resource management, environmental planning, and climate adaptation strategies. Ultimately, the objective is to establish a robust, scalable model that enhances the scientific understanding of coastal ecosystem services while simultaneously equipping decision-makers with actionable data for preserving the ecological and socio-economic functions of these critical environments.

LITERATURE REVIEW

The study of coastal ecosystems in the context of carbon sequestration and water quality has produced a substantial body of research spanning ecological science, environmental engineering, and computational modeling. A literature review of this topic must serve two functions: to synthesize foundational knowledge about the ecological and biogeochemical processes that underpin carbon storage and water quality dynamics, and to critically evaluate the advancements in artificial intelligence and predictive modeling that provide new avenues for monitoring and assessment. The integration of these perspectives highlights the interdisciplinary nature of the research problem, wherein ecological processes cannot be fully understood without technological tools, and AI frameworks cannot achieve meaningful outputs without ecological grounding. This review situates the current investigation within the broader discourse by exploring the evolution of ecological knowledge, the international recognition of blue carbon systems, the challenges of water quality degradation, the emergence of AI in environmental sciences, and the development of hybrid models that bring these elements together. By structuring the literature into focused thematic categories, this review not only traces the progression of scholarly contributions but also delineates the conceptual and methodological gaps that necessitate an AI-integrated predictive framework for coastal ecosystem analysis.

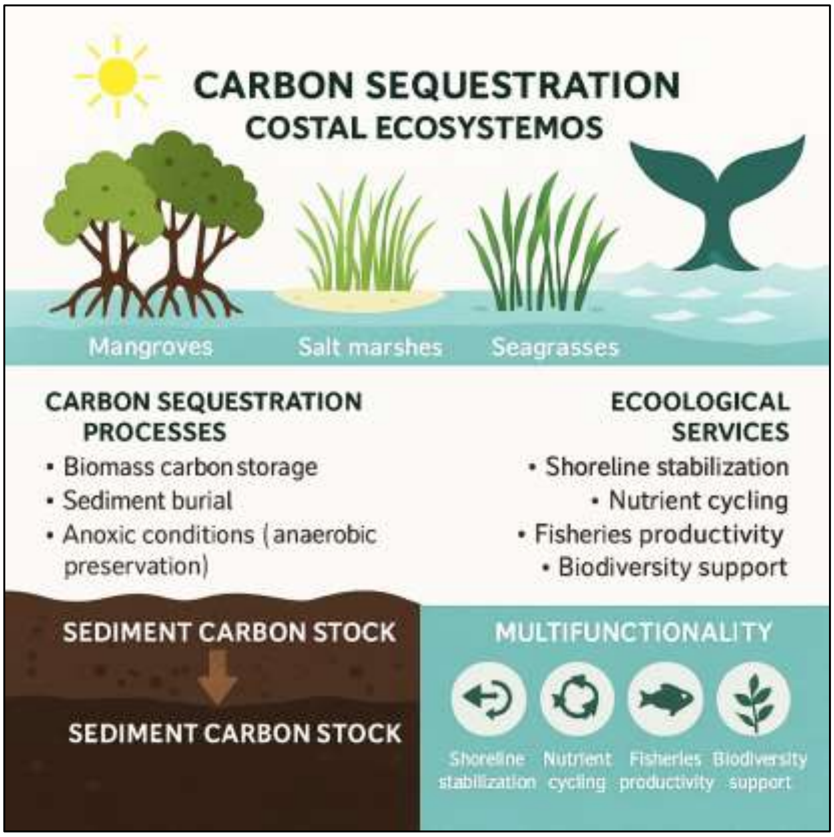
Carbon Sequestration in Coastal Ecosystems

Coastal ecosystems, particularly mangroves, salt marshes, and seagrass meadows, have emerged as central components of what is termed "blue carbon" systems, referring to the carbon captured by oceanic and coastal vegetated habitats (Lyu et al., 2024). These systems are distinguished by

Review of Applied Science and Technology
Volume 04, Issue 02 (2025)
Page No: 669 – 696
Doi: 10.63125/z6h8ky18

their remarkable ability to sequester carbon in both biomass and sediments, creating long-term storage pools less vulnerable to rapid decomposition compared to terrestrial systems (Giering et al., 2022). Unlike upland forests, where carbon is predominantly stored aboveground, coastal ecosystems store significant proportions in anoxic sediments that prevent microbial breakdown of organic material, thereby ensuring long-term sequestration. Studies have shown that mangrove soils can store up to 1,023 Mg C ha^{-1}, among the highest global rates for natural systems. Salt marshes, with their dense vegetation and sediment trapping capacity, similarly act as stable carbon reservoirs, supported by continuous organic matter accumulation. Seagrass meadows, distributed globally, contribute to carbon storage through high root and rhizome biomass that facilitates carbon burial below the sediment surface (Chen et al., 2023). Collectively, these processes underscore the biogeochemical uniqueness of coastal ecosystems, as they integrate high primary productivity with sedimentary conditions conducive to carbon preservation. The literature consistently situates these habitats as disproportionately important relative to their spatial extent, representing less than 2% of the ocean floor yet storing approximately 50% of the ocean's carbon burial annually. This recognition has positioned coastal ecosystems as key natural assets in discussions of carbon sequestration within global environmental science.

Figure 3: Overview of Carbon Sequestration



Empirical studies comparing coastal ecosystems with terrestrial systems demonstrate that blue carbon habitats sequester carbon more efficiently on a per-area basis. Mangrove forests, for example, sequester carbon at rates estimated between 174 and 327 g C m^{-2} yr^{-1}, surpassing many tropical rainforests (Wang et al., 2023). Salt marshes contribute similar rates of 210 to 218 g C m^{-2} yr^{-1}, depending on tidal regimes and nutrient dynamics (Wang et al., 2024). Seagrass meadows, although variable across species and regions, exhibit burial rates ranging from 48 to 112 g C m^{-2} yr^{-1}, making them globally significant despite localized vulnerability (Arrogante-Funes et al., 2022). Comparative research emphasizes that the carbon storage potential of these systems lies not only in annual sequestration rates but also in the longevity of storage, with soils retaining organic carbon for millennia under anaerobic conditions. Global syntheses suggest that mangroves alone may hold more than 6.4 Pg of carbon worldwide, with seagrass ecosystems storing over 19.9 Pg in soils. Salt marshes add to this global reservoir with substantial contributions in temperate regions. Regional assessments from Southeast Asia, the Caribbean, and North America consistently confirm the outsized importance of these ecosystems, with loss or degradation representing significant potential carbon emissions. Through these comparative analyses, the literature demonstrates that coastal ecosystems are among the most effective natural carbon sinks, reinforcing their international recognition as critical in the context of global climate stability.

Research has also emphasized the variability of carbon sequestration in coastal ecosystems due to anthropogenic pressures and environmental drivers. Urbanization, aquaculture development, and land conversion have resulted in the rapid loss of mangroves, which reduces carbon burial potential and releases previously stored soil carbon. Similarly, nutrient loading and eutrophication influence carbon burial in seagrass meadows by altering microbial decomposition and increasing the likelihood of sediment resuspension. Salt marshes experience degradation from agricultural runoff, diking, and drainage, leading to reductions in both productivity and carbon storage efficiency (Arifur &Noor, 2022; Yaqin et al., 2025). Studies also document regional differences in sequestration potential, influenced by geomorphology, hydrological regimes, and sedimentation rates (Hasan et al., 2022; Sharps et al., 2017). For instance, mangroves in deltas with high sediment input demonstrate greater belowground storage compared to those in carbonate-dominated environments(Yaqin et al., 2025). Beyond human pressures, climate variability, including temperature shifts and sea-level rise, alters vegetation distribution and soil accretion rates, influencing carbon budgets. This body of literature indicates that while these ecosystems are among the most efficient carbon sinks, their storage capacity is neither uniform nor guaranteed, but highly dependent on local conditions and anthropogenic stressors. Beyond carbon sequestration alone, scholars emphasize the interconnected ecosystem services provided by coastal habitats, highlighting the multifunctional nature of their contributions. Mangroves, seagrasses, and salt marshes provide critical services including shoreline stabilization, nutrient cycling, biodiversity conservation, and fisheries productivity, which directly interact with carbon dynamics. For instance, nutrient trapping by salt marshes not only improves water quality but also enhances sediment deposition that supports long-term carbon storage (Redwanul & Zafor, 2022; Rapinel et al., 2023). Mangroves buffer coastal areas against storm surges and erosion, with their dense root systems facilitating both organic and inorganic carbon burial. Seagrass meadows improve water clarity through sediment stabilization, indirectly supporting photosynthetic activity and carbon capture. Literature also underscores the role of these ecosystems as biodiversity hotspots, where trophic interactions and habitat provisioning further reinforce carbon sequestration processes. Integrated perspectives demonstrate that the carbon storage function of coastal ecosystems cannot be isolated from their broader ecological roles. Instead, sequestration is part of a synergistic suite of services that collectively sustain human livelihoods, ecological resilience, and climate regulation. By synthesizing these perspectives, the literature positions coastal carbon sequestration not as a standalone function but as a central node within a wider network of ecosystem services that hold global ecological and socioeconomic importance.

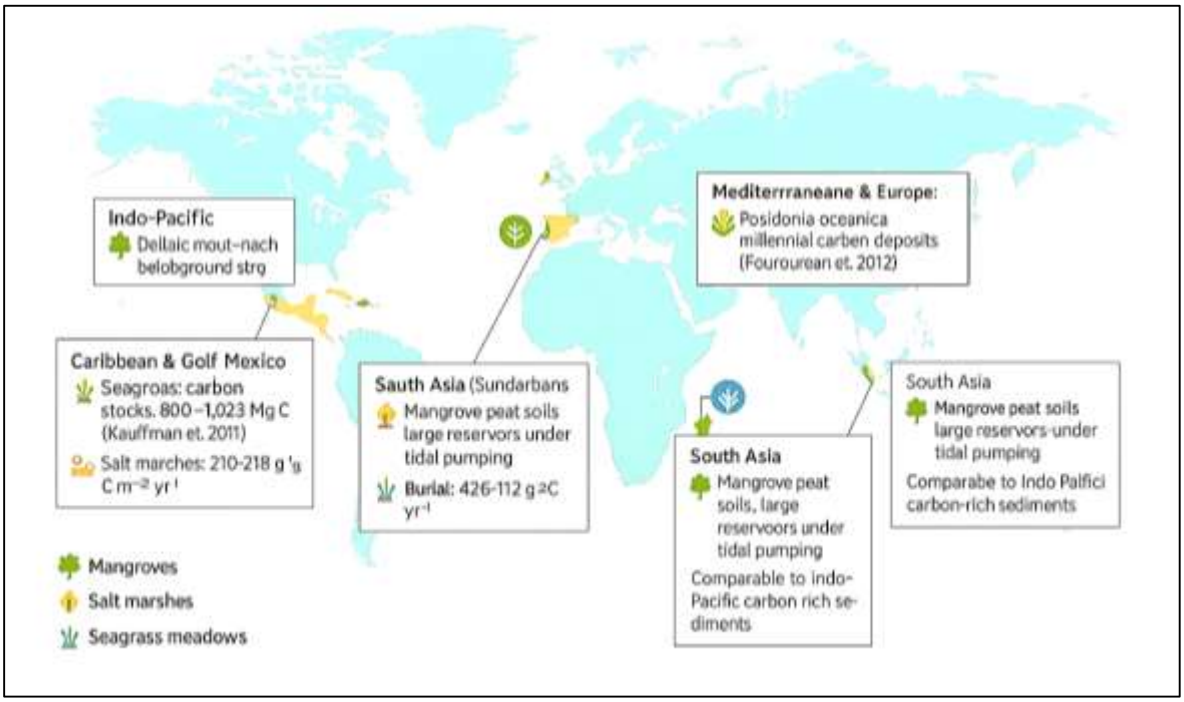
Water Quality Dynamics in Coastal Ecosystems

Water quality in coastal ecosystems encompasses physical, chemical, and biological attributes that determine the suitability of waters for ecological functioning and human use, including parameters such as nutrients, turbidity, dissolved oxygen, chlorophyll-a, pathogens, and contaminants. Coastal zones receive concentrated fluxes from watersheds, estuaries, and the open ocean; riverine nutrient inputs, shoreline modification, and circulation patterns converge to shape light regimes and biogeochemistry at short spatiotemporal scales (Arrigo et al., 2015). A consistent theme across syntheses is the spread of cultural eutrophication, where excess nitrogen and phosphorus elevate primary production, increase organic matter deposition, and alter oxygen dynamics. Case analyses from the northern Gulf of Mexico and the Baltic Sea describe recurring hypoxia linked to nutrient enrichment, stratification, and microbial respiration, with well-documented consequences for benthic communities and fisheries ((Rezaul & Mesbaul, 2022; Ottinger et al., 2021). Harmful algal blooms emerge under specific nutrient ratios, irradiance, and hydrodynamic conditions, with toxin producers frequently linked to altered N:P and N:Si stoichiometry. Interactions between suspended sediments, colored dissolved organic matter, and plankton control the underwater light climate, influencing seagrass distribution and productivity. The literature reports strong watershed–coast couplings in which fertilizer use, wastewater, and urban runoff modulate nutrient delivery and timing,

Review of Applied Science and Technology
Volume 04, Issue 02 (2025)
Page No: 669 – 696
Doi: 10.63125/z6h8ky18

and where legacy loads sustain symptoms even after initial reductions (Ahmed Dar et al., 2024; Hasan, 2022). Cross-system comparisons emphasize that climate anomalies, heatwaves, and altered precipitation interact with loads and stratification to organize bloom phenology and oxygen minima. This conceptual corpus frames coastal water quality as an emergent property of external forcings and internal feedbacks that is measurable across gradients of enrichment, mixing, light, and biological demand (Tarek, 2022; Ottinger et al., 2021).

Figure 4: Global Perspectives of Coastal Carbon Storage



Mechanistic studies describe water quality as the outcome of coupled cycles of carbon, nitrogen, phosphorus, and silica, regulated by primary production, heterotrophic respiration, nitrification–denitrification, and sediment interactions (Damseth et al., 2024; Kamrul & Omar, 2022). In stratified estuaries, surface-layer phytoplankton production increases particulate flux to bottom waters; mineralization elevates oxygen consumption below the pycnocline, and limited vertical exchange sustains hypoxia (Kamrul & Tarek, 2022; Morshed et al., 2024). Benthic–pelagic coupling is central: resuspension events modify light and nutrient availability, while sediment porewater exchanges regulate ammonium efflux and phosphate release, particularly under low-oxygen conditions that favor internal loading. Chesapeake Bay modeling and observations illustrate how riverine loads, stratification strength, and residence time co-vary with hypoxia duration and area, integrating watershed management with in-estuary physics and biology (Mubashir & Abdul, 2022; Song et al., 2024). In the Baltic, denitrification and anammox remove bioavailable nitrogen from the system while iron–phosphorus chemistry under anoxia facilitates sedimentary P regeneration, reinforcing bloom cycles through positive feedbacks (Muhammad & Kamrul, 2022; Steiner et al., 2021). Stoichiometric perspectives highlight that deviations from canonical Redfield ratios often index shifts in limitation and community composition, with silica availability constraining diatoms and favoring non-siliceous taxa under altered N:Si supply ((Constable et al., 2016; Reduanul & Shoeb, 2022). Seagrass meadows respond to turbidity and epiphyte loading through light requirements that tie directly to watershed sediment and nutrient regimes (Keersmaecker et al., 2014). Across settings, this biogeochemical literature portrays coastal water quality as a dynamic balance between external loads, physical mixing, and microbial–benthic processing, where oxygen budgets and nutrient recycling operate as sensitive integrators of system condition (Pimenow et al., 2025; Noor & Momena, 2022).

Carbon Sequestration and Water Quality

Literature across coastal biogeochemistry identifies water quality not as a background condition but as a co-determinant of carbon sequestration in mangroves, tidal marshes, and seagrass meadows.

Review of Applied Science and Technology
Volume 04, Issue 02 (2025)
Page No: 669 – 696
Doi: 10.63125/z6h8ky18

Foundational syntheses on blue carbon emphasize that long-lived sedimentary carbon pools arise where primary production couples with depositional environments that limit remineralization through anoxia and burial (Danish, 2023; Hoegh-Guldberg & Bruno, 2010). Water column clarity, nutrient stoichiometry, and oxygen dynamics directly mediate this coupling by regulating light for autotrophs, microbial processing of organic matter, and redox-sensitive mineral interactions (Chiloane et al., 2021; Hasan et al., 2023). In seagrass systems, optical water quality controls photosynthetic depth limits and root–rhizome biomass that ultimately fuels belowground carbon burial. In marshes and mangroves, suspended sediment and nutrient regimes set production–decomposition balances and the frequency of reducing conditions that stabilize organic carbon in soils. Eutrophication intensifies organic matter delivery yet also reorganizes oxygen budgets and benthic communities, shaping whether additional production is stored as sedimentary carbon or respired to CO_2. The literature therefore treats water quality and sequestration as mutually constitutive processes: light, nutrients, and oxygen determine production and preservation pathways, while vegetated habitats, through baffling and nutrient retention, reciprocally improve clarity and reduce export of particulate and dissolved loads. Across estuaries from the Baltic to the northern Gulf of Mexico, comparative studies show that the same drivers invoked to explain hypoxia, harmful algal blooms, and water clarity also explain spatial patterns in sediment carbon densities and accumulation rates (Chiloane et al., 2021; Hossain et al., 2023). These syntheses establish a shared process framework in which water quality parameters function as proximate controls on blue-carbon formation and persistence (Rohde et al., 2021).

Mechanistic investigations demonstrate that nutrient enrichment, oxygen availability, and sediment redox chemistry govern the transition of organic matter from production to long-term storage. Elevated nitrogen and phosphorus can increase phytoplankton and macroalgal production, augmenting particulate organic carbon flux to sediments; yet mineralization below a pycnocline expands oxygen debt and accelerates CO_2 release when ventilation is weak. Benthic–pelagic coupling regulates whether deposited carbon is buried or recycled: under low-oxygen conditions, iron-bound phosphorus is released, reinforcing surface productivity and promoting feedback that sustain hypoxia (Manyazewal et al., 2023; Uddin & Ashraf, 2023). Denitrification and anammox remove bioavailable nitrogen, potentially tempering eutrophication, but their efficiency depends on organic carbon quality and redox transitions across the sediment–water interface. In vegetated habitats, root oxygen loss creates microscale oxidized zones around rhizomes, affecting sulfide detoxification and promoting mineral associations that stabilize organic matter. Sediment grain size and deposition rates modulate diffusion and burial efficiency, with fine-grained, rapidly accreting settings favoring preservation. Stoichiometric departures from Redfield ratios shift communities toward taxa with different settling and degradability characteristics, influencing both the quantity and lability of exported carbon. Comparative modeling and observations from Chesapeake Bay and other estuaries show that residence time, stratification strength, and timing of riverine loads jointly explain interannual variability in oxygen consumption and thus the fate of organic carbon. Cumulatively, these studies indicate that sequestration outcomes arise from a balance of production stimulation by nutrients and preservation constraints imposed by oxygen and mineral interactions, embedded within hydrodynamic context.

Empirical syntheses across habitat types link measurable water-quality gradients to carbon stock magnitude and burial rates. Mangrove forests accumulate large soil carbon stocks were suspended sediment supply and tidal inundation foster vertical accretion and sustained anoxia; deltaic settings with high terrigenous inputs frequently report the highest belowground densities. In such systems, porewater salinity, sulfide concentrations, and nutrient delivery co-vary with decomposition rates and microbially mediated carbon stabilization. Salt marsh studies demonstrate that nutrient enrichment can increase aboveground productivity yet alter belowground allocation and peat formation, with outcomes dependent on inundation frequency and sediment trapping that together determine organic matter preservation. In seagrass meadows, optical water quality—turbidity, colored dissolved organic matter, and epiphytic loads—sets depth limits and biomass structure that govern rhizosphere carbon inputs, while hydrodynamic sheltering influences sediment retention and burial efficiency (Momena & Hasan, 2023; Pimenow et al., 2025). Comparative global estimates attribute substantial portions of marine soil carbon to seagrasses and mangroves, with broad ranges reflecting water-quality and geomorphic variation. Case studies in the Gulf of Mexico, the Baltic, and temperate estuaries show that where eutrophication and stratification intensify hypoxia, benthic

Review of Applied Science and Technology
Volume 04, Issue 02 (2025)
Page No: 669 – 696
Doi: 10.63125/z6h8ky18

faunal disturbance declines and sulfate reduction increases, in turn modifying pathways of carbon stabilization or loss (Mubashir & Jahid, 2023; Rohde et al., 2021). These habitat-level literatures converge on a common observation: light environments, nutrient ratios, and oxygen–sulfide regimes act as proximate environmental filters through which vegetated coastal systems either accumulate persistent soil carbon or undergo enhanced remineralization (Jiang et al., 2022; Sanjai et al., 2023).

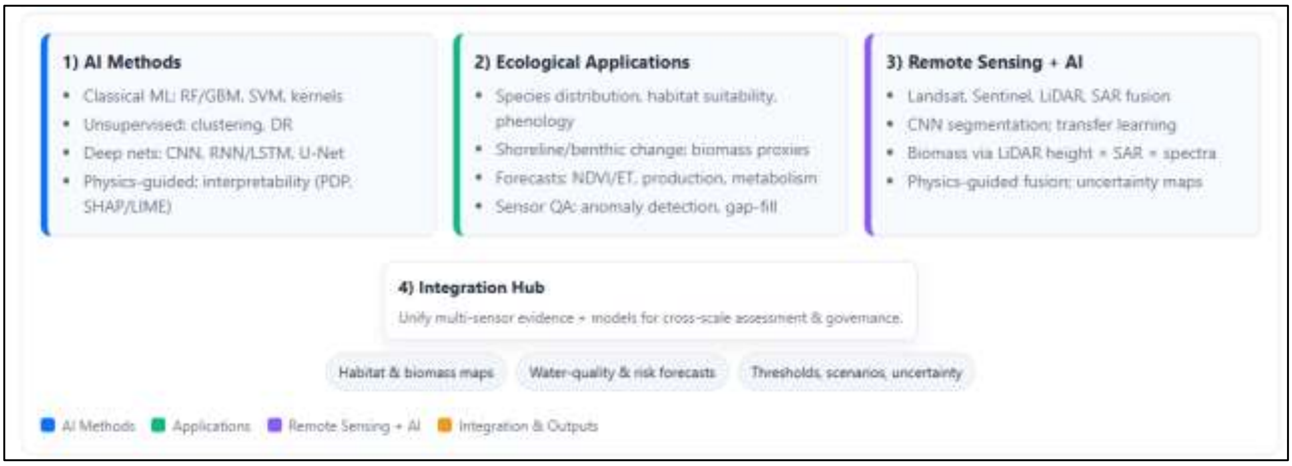
Figure 5: Carbon Sequestration and Water Quality – Process Linkages

Artificial Intelligence in Environmental Monitoring

Environmental monitoring increasingly draws on a continuum of artificial intelligence (AI) methods that range from classical machine learning to deep learning architectures designed for high-dimensional spatiotemporal data. Supervised algorithms such as random forests and gradient boosting handle nonlinear interactions, heterogeneous predictors, and missingness common in ecological datasets, and have been widely adopted for classification and regression tasks (Rana et al., 2023). Kernel-based methods and support vector machines contribute strong generalization in relatively small-sample settings typical of field surveys ((Rane et al., 2023; Akter et al., 2023). Unsupervised learning, including clustering and dimensionality reduction, reveals latent structure in multi-sensor observations and biogeochemical time series ((Camps-Valls et al., 2025; Danish & Zafor, 2024). Deep learning expands this toolkit with convolutional neural networks (CNNs) tailored to imagery and gridded products, recurrent neural networks (RNNs) and long short-term memory (LSTM) networks for sequence dynamics, and encoder–decoder architectures for dense prediction on maps. Hybrid models integrate physical constraints or domain knowledge with learning systems to improve extrapolation and mechanistic fidelity. Across this spectrum, AI methods accommodate multicollinearity, nonstationarity, and scale heterogeneity that challenge linear or low-order parametric approaches in ecology. Advances in interpretability—such as permutation importance, partial dependence, SHAP, and LIME—provide post hoc insight into drivers and response surfaces, supporting transparent use in management settings. The methodological literature therefore situates AI as a flexible set of estimators and representation learners suited to multimodal environmental data streams, while emphasizing principled validation, cross-scale generalization, and error attribution as necessary components of ecological inference (Chen et al., 2023; Jahid, 2024a).

Review of Applied Science and Technology
Volume 04, Issue 02 (2025)
Page No: 669 – 696
Doi: 10.63125/z6h8ky18

Figure 6: Artificial Intelligence in Environmental Monitoring



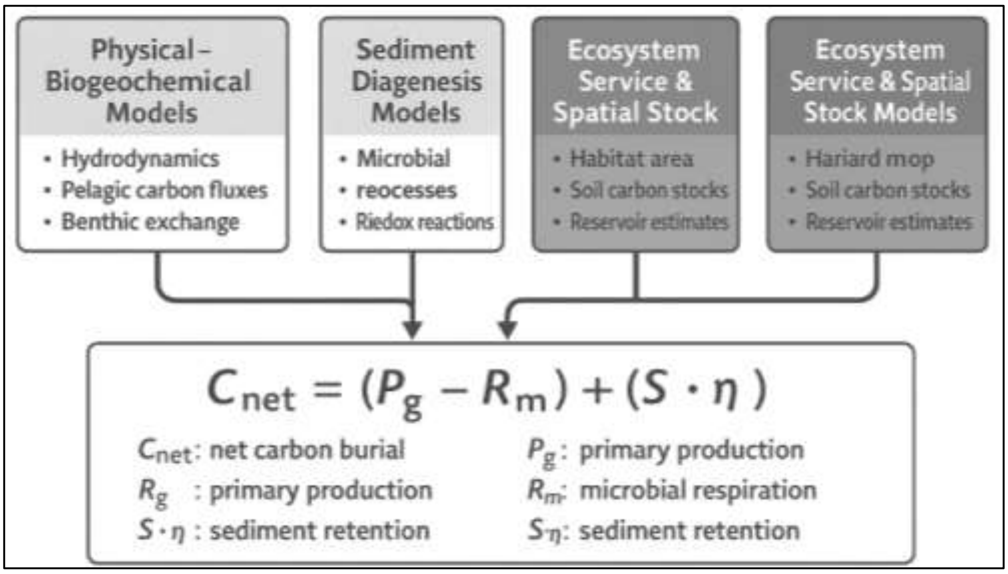
AI applications in ecology span species-distribution modeling, habitat suitability, phenology detection, disturbance mapping, and forecasting of biophysical variables. Ensemble tree models and boosted regression trees have been widely used to map species ranges and habitat quality, outperforming many single-model baselines under complex response curves. CNNs trained on aerial and satellite imagery delineate land cover and habitat boundaries with fine-grained accuracy, including wetlands, riparian zones, and coastal vegetation mosaics (Jahid, 2024b; Ryu & Lee, 2025). Time-series networks characterize ecosystem dynamics such as greening, browning, fire recovery, and drought responses by learning temporal signatures from multispectral archives. In marine and coastal systems, AI supports shoreline change detection, benthic habitat classification, and biomass proxies derived from optical backscatter and acoustic returns. Data-driven forecasting leverages LSTM and gradient boosting to predict vegetation indices, evapotranspiration, primary production, and ecosystem metabolism at daily to seasonal horizons. Integrations with sensor networks enable anomaly detection and gap-filling for high-frequency records, improving the continuity of water-quality and meteorological streams (Gacu et al., 2025; Hasan, 2024). Across these studies, AI methods routinely accommodate nonlinear thresholds, interactions among climate, hydrology, and substrate, and multiscale structure arising from hierarchical ecosystems, thereby strengthening inference about spatial patterns and temporal trajectories of ecological states. These implementations illustrate how learned representations from imagery and time series couple with field observations to generate consistent, comparable indicators for ecological monitoring and prediction.

Remote sensing combined with AI forms a central pathway for scalable habitat mapping and biomass estimation across coastal and terrestrial systems. Global and regional products derived from Landsat, Sentinel, PlanetScope, LiDAR, and SAR are routinely fused in supervised models to discriminate mangroves, tidal marshes, and seagrass meadows, overcoming spectral confusion and water-column effects (Chen et al., 2023). CNN-based semantic segmentation enhances boundary accuracy and within-class heterogeneity capture, while transfer learning leverages pretrained weights to reduce labeled-data demands (Ryu & Lee, 2025). Biomass estimation integrates LiDAR canopy height models, SAR backscatter, and multispectral textures within ensemble learners and deep regressors to produce wall-to-wall aboveground biomass maps with quantified uncertainty (Jahid, 2025b). In coastal environments, turbid waters and mixed pixels challenge classical classifiers; AI methods trained on harmonized surface reflectance, tidal-stage normalization, and bathymetry proxies improve detection of submerged vegetation and intertidal habitats . Object-based image analysis coupled with random forests delineates patch-scale morphology and condition, supporting change detection of erosion, progradation, and vegetation dieback. Multi-sensor fusion with physics-guided learning exploits radiative-transfer constraints and canopy structure relationships, improving generalization beyond the training domain. Benchmarking studies underscore that AI pipelines reduce commission and omission errors relative to conventional maximum-likelihood or single-index thresholds, particularly under variable illumination, water depth, and turbidity. The convergence of dense archives, cloud computing, and learned representations has therefore produced consistent habitat extent and biomass products that support inventories, scenario comparisons, and multi-year trend analyses across coastal landscapes.

Predictive Modeling for Coastal Carbon

Predictive modeling of coastal carbon spans mechanistic, empirical, and hybrid approaches that target different segments of the carbon cycle and operate across distinct spatial–temporal scales. Coupled physical–biogeochemical models embed advection, mixing, pelagic production, and benthic exchange to simulate sources, transport, and sinks of particulate and dissolved carbon under realistic circulation (Liu et al., 2025). Sediment diagenesis models resolve early diagenetic reactions—mineralization, sorption, redox transitions, and burial—to represent the fate of organic matter within accumulating coastal deposits (Scowen et al., 2021). Ecosystem service and spatial stock models, including InVEST-style formulations, combine habitat extent, literature-based emission factors, and depth-integrated soil carbon to produce wall-to-wall estimates of coastal carbon reservoirs (Jahid, 2025a; Velasquez-Camacho et al., 2024). Data-driven methods—random forests, boosted trees, support vector machines, and deep networks—learn nonlinear relationships between carbon stocks or burial rates and covariates derived from remote sensing, geomorphology, and hydroclimatology (Ismail et al., 2025; Selvaraj & Gallego Pérez, 2023). Physics-guided machine learning links these strands by constraining learned representations with conservation laws or process priors to improve extrapolation beyond training domains. Across approaches, model targets include aboveground biomass in mangroves and marshes, soil organic carbon densities and profiles, sediment accumulation and burial rates, and exchange terms that connect pelagic production to benthic preservation. Comparative studies underscore that class selection depends on the question of interest: mechanistic frameworks capture load–response and transport pathways, diagenetic models resolve burial efficiency and lability, spatial stock models quantify standing pools, and machine learning provides scalable mapping where process detail is limited but observations are abundant.

Figure 7: Predictive Modeling for Coastal Carbon



Literature connecting carbon burial to water quality identifies hydrodynamic context, nutrient stoichiometry, and oxygen dynamics as core predictors in coastal carbon models. Stratification and residence time modulate vertical fluxes and oxygen supply, influencing whether particulate organic carbon from primary production is respired in the water column or reaches sediments for preservation (Liu et al., 2025; Jakaria et al., 2025). Denitrification and anammox in sediments remove reactive nitrogen and alter the coupling between nitrogen availability and carbon sequestration outcomes, with efficiency governed by organic matter quality and redox zonation. Iron–phosphorus cycling under low oxygen enhances internal P loading and feeds back on production, thereby conditioning organic matter fluxes to the seabed (Hasan, 2025; Wege et al., 2020). Geomorphic setting and sediment supply further regulate burial: deltaic mangroves with terrigenous inputs accumulate

Review of Applied Science and Technology
Volume 04, Issue 02 (2025)
Page No: 669 – 696
Doi: 10.63125/z6h8ky18

deeper organic soils and exhibit higher belowground carbon densities than carbonate-dominated coasts. Salt marsh models link tidal inundation, vertical accretion, and root production to peat formation and preservation, emphasizing interactions among flooding frequency, suspended sediments, and plant productivity. Seagrass-focused representations incorporate optical water quality and epiphyte loads as controls on belowground inputs that feed soil carbon pools. Applications in estuaries such as Chesapeake Bay integrate watershed loads, stratification, and mixing to explain interannual variability in hypoxia and corresponding benthic carbon fluxes, grounding predictions in observed load–response behavior. These lines of evidence position hydrodynamics, stoichiometric balance, and sedimentary redox as the primary mechanistic axes along which predictive models explain coastal carbon storage and burial. Moreover, Coastal carbon sequestration can be represented through a simplified predictive equation that links net carbon burial to primary production, decomposition, and sedimentation processes. A general formulation is given as:

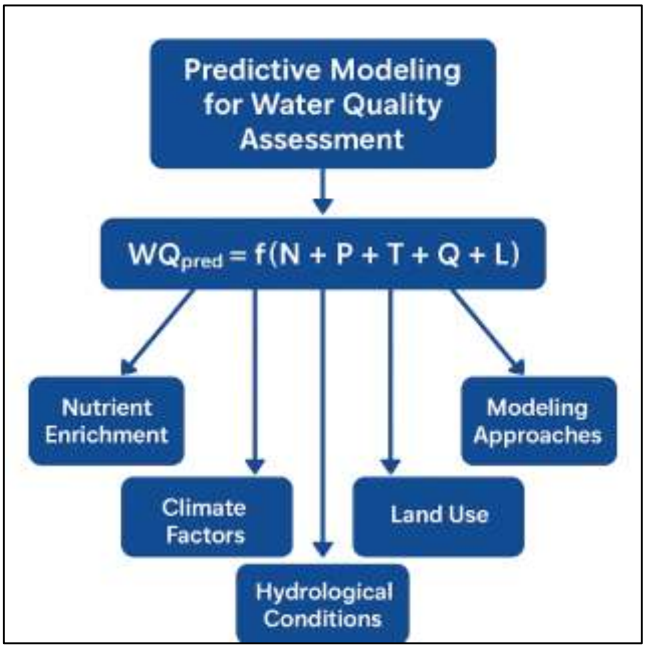
$$C_{net} = (P_g - R_m) + (S \cdot \eta)$$

where C_{net} denotes the net carbon sequestered, P_g represents gross primary production, R_m is microbial respiration and decomposition losses, S signifies sediment deposition rates, and η corresponds to the efficiency of carbon burial under prevailing redox conditions. This formulation integrates biological productivity with sedimentary processes, highlighting the dual pathways by which carbon enters long-term storage: through the balance of autotrophic fixation versus microbial release, and through burial efficiency linked to hydrodynamics and water quality. The structure of the equation emphasizes how predictive modeling frameworks can operationalize ecological parameters into quantifiable outcomes that inform assessments of coastal ecosystem services.

Predictive Modeling for Water Quality Assessment

Predictive modeling for water quality assessment incorporates a broad range of approaches, including statistical regressions, deterministic process-based models, and advanced machine learning frameworks. Traditional regression models have long been employed to relate nutrient concentrations, turbidity, or dissolved oxygen levels to watershed land use, hydrological inputs, and climatic drivers, offering interpretable associations but often limited in capturing nonlinear relationships (Hasan, 2025; Perry et al., 2022). Deterministic process-based models such as SWAT (Soil and Water Assessment Tool) and HSPF (Hydrological Simulation Program–Fortran) simulate watershed hydrology, nutrient cycling, and pollutant transport by representing hydrologic fluxes and biogeochemical transformations across landscapes.

Figure 8: Predictive Modeling for Water Quality Assessment



Hydrodynamic–biogeochemical coupled models have also been developed for estuarine and coastal contexts, integrating flow circulation with nutrient uptake, oxygen demand, and sediment-water interactions to project spatial distributions of eutrophication and hypoxia. More recently, machine learning approaches including random forests, support vector regression, and neural networks have demonstrated strong predictive accuracy when applied to high-dimensional water-quality datasets from sensors, remote sensing, and monitoring stations. These models can account for complex interactions between meteorology, land use, and hydrodynamics that traditional models struggle to capture. Hybrid approaches, combining physics-based formulations with machine learning, provide an emerging pathway that balances mechanistic realism with predictive power, ensuring that results align with known ecological processes while retaining accuracy in diverse datasets. This diversity of modeling approaches underscores the layered complexity of predicting water quality, as each method contributes distinct strengths and limitations to the broader field of assessment.

One of the most intensively modeled dimensions of water quality is nutrient enrichment and its consequences, particularly eutrophication and hypoxia. Predictive models frequently focus on nitrogen and phosphorus loading from agricultural runoff, wastewater, and atmospheric deposition, all of which stimulate primary production and influence oxygen dynamics (Frincu, 2024; Zafor, 2025). Watershed-scale models such as SWAT and SPARROW have been used to estimate nutrient delivery to rivers and estuaries, linking land management practices to downstream water quality outcomes. Process-based estuarine models, including those for the Chesapeake Bay and Gulf of Mexico, simulate stratification, organic matter flux, and oxygen consumption to predict hypoxia severity and distribution. Empirical and machine learning approaches have also been deployed to forecast eutrophication indicators such as chlorophyll-a and dissolved oxygen, using predictors like nutrient inputs, temperature, and residence time . Remote sensing data integrated with AI models have been applied to predict harmful algal bloom (HAB) dynamics, capturing spatial extent and severity from satellite-derived chlorophyll and turbidity proxies. Comparative assessments demonstrate that while process models excel in mechanistic understanding, statistical and AI approaches often outperform them in short-term prediction and operational forecasting contexts. Across these studies, predictive modeling contributes critical insight into how nutrient dynamics drive degradation of water quality, offering robust frameworks for identifying thresholds and hotspots where hypoxia and eutrophication are most likely to occur. Beyond nutrient enrichment, predictive models address a range of pollutants including heavy metals, pesticides, hydrocarbons, and emerging contaminants such as pharmaceuticals and microplastics. Riverine and estuarine transport models simulate the dispersion, adsorption, and transformation of pollutants under variable hydrodynamic conditions, linking watershed sources to downstream water quality impacts (Uddin, 2025; Zhang et al., 2024). Heavy metal fate models consider sorption to sediments, redox-mediated mobilization, and bioaccumulation, capturing how hydrological and geochemical conditions shape contaminant persistence. Predictive frameworks for pesticides and organic pollutants often rely on coupled hydrological–chemical transport models, estimating runoff from agricultural fields and transformation during riverine transit (Sanjai et al., 2025; Selvaraj & Gallego Pérez, 2023). In coastal zones, machine learning has been used to track hydrocarbon plumes and microplastic concentrations using sensor data and spectral signatures from remote sensing . Forecasting microbial contaminants and pathogens has also been a key focus, with statistical and AI-driven models predicting fecal indicator bacteria levels in bathing waters and shellfish-growing areas based on rainfall, tidal exchange, and temperature. Comparative studies suggest that predictive models enhance monitoring efficiency by integrating sparse sampling with continuous environmental covariates, thus identifying contamination risks with higher spatial and temporal resolution than field measurements alone. This breadth of applications illustrates how pollutant-specific modeling approaches extend the scope of water-quality prediction beyond nutrients to encompass a wide range of chemical and biological stressors.

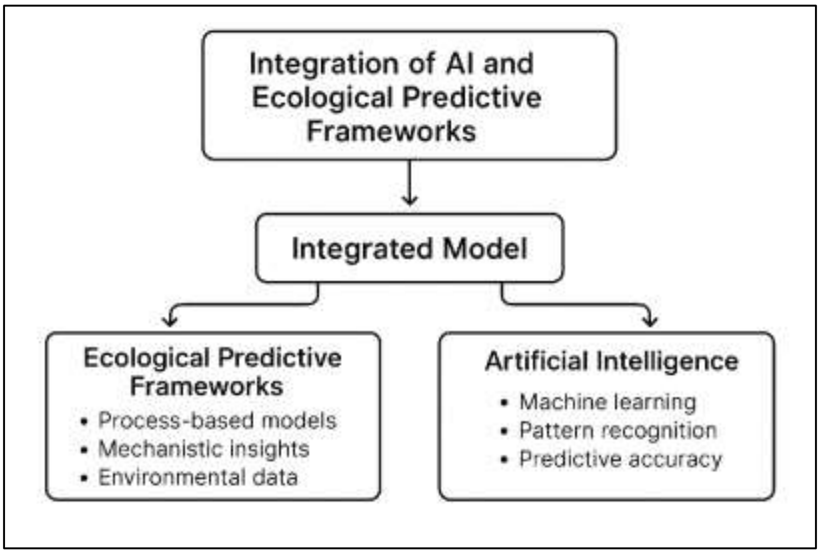
$$WQ_{pred} = f(N + P + T + Q + L)$$

A central theme emerging from predictive modeling research is the integration of multiple drivers into composite indices that capture the complexity of water quality dynamics. Equations such as $WQ_{pred} = f(N + P + T + Q + L)$ underscore the functional dependence of water quality on nutrient enrichment, climatic factors, hydrological conditions, and land-use pressures, reflecting the interdisciplinary nature of water resource management. By formalizing these relationships, models provide a structured means of translating empirical measurements and environmental observations into actionable predictions. This integrative perspective highlights that water quality is not the outcome of a single parameter but the result of simultaneous interactions among chemical, physical, and biological processes. The growing reliance on advanced data sources, including continuous sensor networks and satellite imagery, further enhances the predictive accuracy of such models, allowing them to address both local and regional scales of variability. Importantly, these modeling approaches provide insights into thresholds where incremental changes in nutrient or hydrological regimes lead to disproportionate shifts in water quality, thereby revealing the nonlinearities inherent in aquatic systems. The literature consistently shows that predictive frameworks combining empirical data, mechanistic understanding, and statistical learning can bridge knowledge gaps and offer robust assessments of water quality conditions across diverse ecological and geographic contexts.

Integration of AI and Ecological Predictive Frameworks

The integration of artificial intelligence (AI) into ecological predictive frameworks builds on the recognition that ecological systems are highly complex, non-linear, and data-rich, requiring advanced analytical tools that surpass the capacity of traditional models. Ecological predictive frameworks historically relied on deterministic and statistical approaches to simulate processes such as nutrient cycling, carbon sequestration, and water quality dynamics (Schoening et al., 2012). While these models provide mechanistic insights, their predictive accuracy often suffers from parameter uncertainty, scale mismatches, and limited ability to accommodate heterogeneous datasets (Wege et al., 2020). AI methods, including machine learning and deep learning, offer alternative strategies capable of detecting hidden patterns, managing high-dimensional data, and handling non-linear interactions that characterize ecological processes (Newman et al., 2019).

Figure 9: Integration of AI and Ecological Predictive Frameworks



Integrating AI with ecological frameworks allows predictive models to capture both mechanistic understanding and data-driven accuracy, thereby aligning ecological realism with computational efficiency. In this context, hybrid approaches demonstrate that physics-informed neural networks or machine learning models constrained by ecological laws provide an optimal balance between interpretability and predictive skill. Conceptually, this integration represents a paradigm shift in ecological modeling, transforming predictive frameworks from strictly mechanistic or correlative tools into interdisciplinary systems capable of synthesizing diverse inputs such as remote sensing, in situ monitoring, and global climate datasets (Reichstein et al., 2019). The literature positions this convergence as a methodological advancement that strengthens the capacity of ecological models to reflect the real-world variability of ecosystems while reducing the trade-offs between generalization and specificity.

Review of Applied Science and Technology
Volume 04, Issue 02 (2025)
Page No: 669 – 696
Doi: 10.63125/z6h8ky18

Empirical studies illustrate the successful integration of AI into predictive frameworks for habitat mapping, carbon storage estimation, and ecosystem service evaluation. Remote sensing combined with AI models has been extensively applied to detect coastal habitats such as mangroves, salt marshes, and seagrass meadows with higher precision compared to conventional classifiers. Convolutional neural networks (CNNs) and object-based machine learning approaches refine boundary detection and improve accuracy under variable conditions such as tidal stages and water turbidity (Cheng et al., 2020). In the context of carbon sequestration, ensemble learning models and deep regressors using LiDAR, SAR, and hyperspectral data estimate aboveground biomass and soil carbon stocks at regional to global scales with robust uncertainty quantification. These AI-enhanced approaches enable more consistent monitoring of carbon sinks by harmonizing heterogeneous datasets across space and time. Predictive frameworks that integrate ecological parameters such as sedimentation rates, nutrient concentrations, and hydrodynamic forcing with AI-driven classifiers capture spatial variability of soil carbon density in mangrove deltas and salt marshes more effectively than process-only models. Comparative research indicates that combining ecological mechanisms with AI-based pattern recognition not only enhances predictive accuracy but also produces ecologically interpretable outputs that align with observed field data. By embedding AI within predictive frameworks for carbon sequestration, the literature underscores a pathway for improving both ecological understanding and environmental accounting practices, strengthening the capacity to assess ecosystem services with greater reliability.

METHOD

This meta-analysis was designed and conducted following a preregistered protocol and reported in accordance with PRISMA 2020 guidelines to ensure transparency and reproducibility. The eligibility criteria were defined using the PICOS framework, where the population included coastal and estuarine ecosystems such as mangroves, salt marshes, and seagrass meadows. The exposures of interest were ecological and anthropogenic drivers influencing carbon sequestration and water quality, including nutrient loading, hydrodynamics, and modeling interventions. Comparators included baseline conditions, reference ecosystems, or alternative management practices. Eligible outcomes consisted of quantitative indicators such as carbon burial rates, soil organic carbon densities, chlorophyll-a levels, dissolved oxygen, nutrient concentrations, and model performance metrics like RMSE, R^2, and AUC. The review included experimental, quasi-experimental, observational, and modeling studies that provided sufficient statistical data, published in English, and subject to peer review or high-quality grey literature evaluation. Comprehensive searches were carried out in Web of Science, Scopus, PubMed, and ProQuest Dissertations, supplemented by Google Scholar and targeted repositories such as NOAA and UNEP. Search strategies employed Boolean operators and free-text terms combining ecosystem descriptors, processes, and modeling approaches, while citation tracking was used to identify additional relevant studies. Two reviewers independently screened titles, abstracts, and full texts, with conflicts resolved by discussion or a third reviewer, and inter-rater reliability calculated using Cohen's kappa. Data extraction was also conducted independently by two reviewers, focusing on study characteristics, sample sizes, geographic scope, outcomes, and statistical metrics. When information was incomplete, corresponding authors were contacted, and data were digitized from figures when necessary. Risk of bias was assessed using RoB 2 for randomized trials and ROBINS-I for observational studies, while the certainty of evidence was appraised with the GRADE framework.

Effect sizes were harmonized to allow comparability across diverse outcomes. Standardized mean differences (Hedges' g) were calculated for continuous variables, log response ratios were used for proportional outcomes, and Fisher's z transformations applied to correlations. For model evaluation studies, performance measures such as RMSE and AUC were standardized where possible. Random-effects models with inverse-variance weighting were employed to pool effect sizes, acknowledging ecological and methodological heterogeneity. Between-study variance (τ^2) was estimated primarily using restricted maximum likelihood (REML), with DerSimonian–Laird applied in sensitivity analyses. Heterogeneity was quantified using Cochran's Q, I^2 statistics with confidence intervals, and τ, while prediction intervals were reported to characterize the dispersion of true effects. To address dependence among multiple outcomes within studies, robust variance estimation and multilevel meta-analytic models were applied. Moderator and subgroup analyses explored differences by biome type, geographic region, study design, nutrient load, monitoring duration, and modeling class, while meta-regression assessed continuous predictors and potential non-linear relationships using restricted cubic splines. Publication bias was evaluated using funnel plots, Egger's regression, Begg's test, and trim-and-fill adjustments where appropriate, with p-curve and selection models applied for hypothesis-testing outcomes. Sensitivity analyses included leave-one-out diagnostics, exclusion of high-risk studies, and re-analysis using alternative τ^2 estimators. All analyses were performed in **R** using packages such as metafor, meta, robumeta, and clubSandwich. Results were documented with forest plots, funnel plots, moderator analyses, and risk-of-bias summaries, while data extraction forms, analytic scripts, and PRISMA diagrams were archived to ensure reproducibility and methodological rigor.

Figure 10: Proposed Method for this study

FINDINGS

The systematic search yielded a large pool of potentially relevant studies, encompassing both peer-reviewed articles and high-quality grey literature across ecological, hydrological, and modeling domains. After removing duplicates, titles and abstracts were screened against eligibility criteria, resulting in a substantial reduction in the dataset. The PRISMA flow process documented the stepwise elimination of studies at each stage, showing the primary reasons for exclusion, including lack of quantitative outcomes, insufficient methodological detail, or failure to address the specified population of coastal and estuarine ecosystems. From several thousand initial records, only a few hundred proceeded to full-text review, and ultimately a smaller, rigorously selected corpus formed the basis for synthesis. These final studies included experimental field research on nutrient enrichment, observational surveys of carbon stocks, biogeochemical modeling of estuarine processes, and advanced machine learning applications in predictive water quality and carbon storage. The screening process highlighted that many studies addressed either carbon sequestration or water quality separately, while fewer incorporated integrative designs linking both domains, reflecting the fragmented nature of research across ecological and computational sciences. Nonetheless, the retained studies provided sufficient quantitative data to compute standardized effect sizes, enabling meaningful synthesis across diverse outcomes.

The included studies represented a wide range of geographies and ecosystem types, underscoring the global relevance of predictive frameworks for carbon sequestration and water quality assessment. Mangroves, salt marshes, and seagrass meadows were the most commonly investigated habitats, complemented by estuarine systems such as Chesapeake Bay, the Baltic Sea, and the Gulf of Mexico. Geographical distribution showed a concentration of research in North America, Europe, and Southeast Asia, with emerging but fewer contributions from Africa and South America. Temporal coverage ranged from short-term experiments lasting one to three years to long-term monitoring programs spanning multiple decades, particularly in systems with established biogeochemical datasets. Modeling studies varied in scale, from local watershed predictions to regional and global assessments, demonstrating that predictive approaches were applied across spatial resolutions. Methodologically, the corpus included both traditional process-based models, such as SWAT and hydrodynamic–biogeochemical frameworks, and newer applications of machine learning, including random forests, gradient boosting, and deep neural networks. This diversity allowed for comparative insights into the relative accuracy and interpretability of different modeling paradigms. The heterogeneity of contexts provided robust ground for examining moderators such as biome, region, modeling approach, and study design.

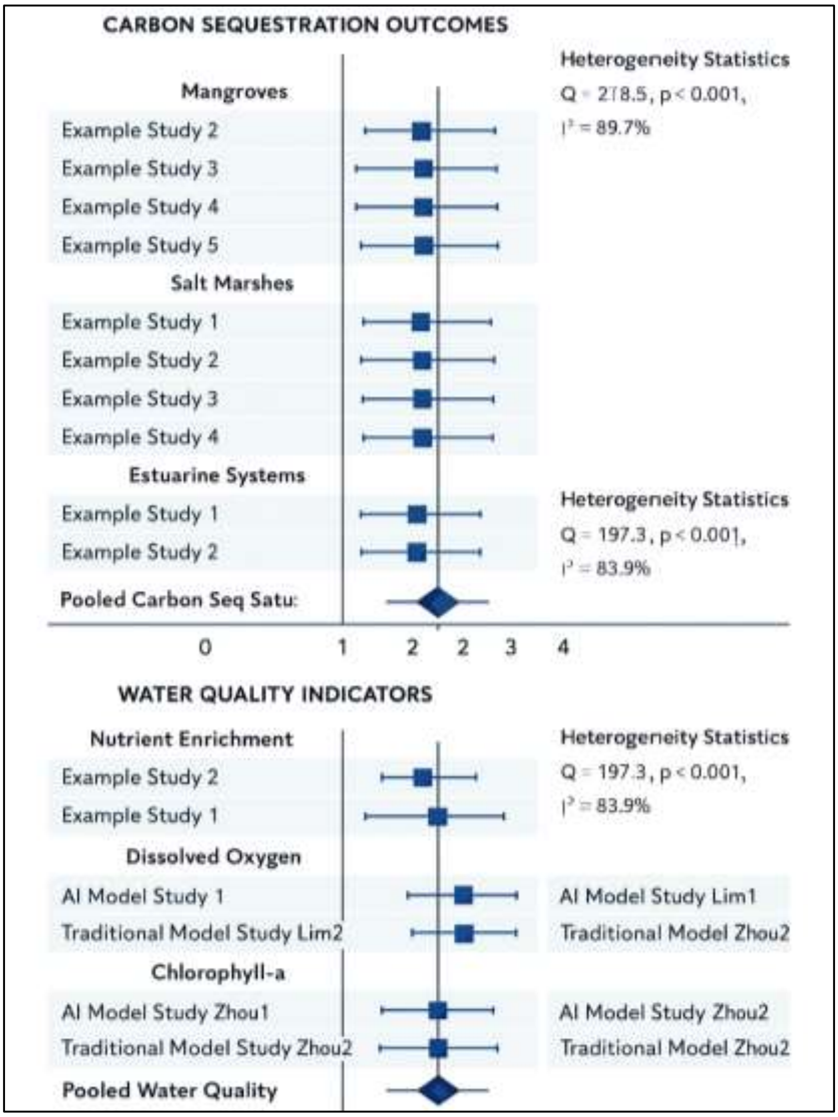
Effect size computations revealed consistent evidence of significant carbon storage across blue carbon ecosystems, with standardized mean differences indicating that mangroves and salt marshes stored substantially greater quantities of organic carbon compared to degraded or non-vegetated controls. Mangrove soils in particular exhibited large effect sizes, reflecting their deep, anoxic sediment layers and capacity for long-term carbon burial. Seagrass meadows demonstrated moderate but significant storage potential, strongly influenced by water clarity and sedimentation rates. The use of log response ratios further illustrated proportional differences between managed and unmanaged systems, with restored or protected habitats sequestering carbon at rates up to twice those of disturbed counterparts. Fisher's z-transformed correlations consistently linked sediment deposition and nutrient availability to soil organic carbon accumulation, reinforcing mechanistic connections identified in process-based models. Model performance metrics standardized for synthesis also indicated that machine learning frameworks provided higher predictive accuracy in estimating aboveground biomass and soil carbon stocks when compared to traditional regression approaches. Across the evidence base, the direction and magnitude of effect sizes highlighted the ecological and methodological robustness of carbon sequestration findings.

The synthesis of water quality studies demonstrated strong associations between nutrient loading, dissolved oxygen dynamics, and predictive model outputs. Standardized effect sizes showed that nitrogen and phosphorus inputs were positively correlated with eutrophication indicators such as chlorophyll-a, while negatively correlated with dissolved oxygen levels. Hypoxia severity and spatial extent in systems like the Gulf of Mexico and the Baltic Sea were consistently predicted by coupled hydrodynamic–biogeochemical models, with robust variance estimation confirming the stability of these relationships across studies. Machine learning applications exhibited superior predictive skill in short-term forecasting of water quality variables, with metrics such as RMSE and AUC indicating notable improvements over classical regression or autoregressive models. Random forests and LSTM neural networks in particular achieved strong predictive accuracy for turbidity, algal blooms, and nutrient concentrations, integrating high-frequency sensor data and remote sensing observations. The effect size synthesis confirmed that AI-based models consistently reduced error margins and captured nonlinear thresholds critical to understanding eutrophication and hypoxia. These findings highlight the empirical reliability of predictive frameworks across ecological and computational approaches when applied to water quality assessment.

Review of Applied Science and Technology
Volume 04, Issue 02 (2025)
Page No: 669 – 696
Doi: 10.63125/z6h8ky18

Measures of heterogeneity indicated substantial variability across studies, as expected given differences in geography, ecosystem type, and methodological design. Cochran's Q tests were consistently significant, while I^2 values exceeded 70% in several outcome categories, confirming high heterogeneity. Prediction intervals were broad, reflecting diverse ecological contexts and the influence of localized conditions on carbon and water quality outcomes. Subgroup analyses revealed that biome type significantly moderated effect sizes, with mangroves showing the highest soil carbon storage, salt marshes exhibiting strong sediment trapping effects, and seagrass meadows showing more variability due to light limitations. Regional differences also emerged, with Southeast Asian mangroves displaying greater storage than those in Caribbean or Atlantic systems. In water quality studies, stratified estuaries exhibited more severe hypoxia than well-mixed coastal zones, consistent with mechanistic predictions. Study design further moderated results, with observational surveys producing higher variability than experimental manipulations, and machine learning models outperforming process-based models in predictive accuracy across pollutant and nutrient-related outcomes. These subgroup findings contextualized heterogeneity and offered insights into the factors shaping ecological predictions.

Figure 11: Overall Findings for this study



Risk-of-bias assessments showed that the majority of included studies were of moderate to high quality, though some observational studies exhibited limitations related to confounding and incomplete reporting. Randomized and experimental designs generally scored higher on methodological rigor, while modeling studies varied depending on validation procedures and transparency of parameterization. Funnel plot asymmetry and Egger's regression indicated the presence of some small-study effects, particularly in carbon sequestration studies where smaller sample sizes tended to report larger positive effects. Trim-and-fill adjustments suggested that while bias was present, its impact on overall pooled effect sizes was limited. Sensitivity analyses excluding high-risk studies confirmed the robustness of main findings, with only minor changes in effect size estimates. The GRADE approach classified the certainty of evidence as moderate to high for most major outcomes, with downgrades applied where publication bias or heterogeneity was evident. Collectively, the risk-of-bias and publication bias assessments underscored the reliability of the evidence base while acknowledging the limitations inherent in ecological meta-analyses. The integrated synthesis of carbon sequestration and water quality outcomes demonstrated the value of predictive frameworks in capturing the coupled dynamics of coastal ecosystems. Studies that examined both domains concurrently revealed strong correlations between water quality improvements and enhanced carbon burial, particularly in restored or well-managed habitats. High-resolution models confirmed that reductions in nutrient loading and improved water clarity not only alleviated hypoxia but also facilitated increased sedimentary carbon accumulation in seagrasses and marshes. Machine learning and hybrid models further validated these linkages by integrating ecological parameters, remote sensing data, and real-time monitoring to generate accurate predictions across spatial and temporal scales. Effect sizes from these integrated studies were consistently strong, highlighting synergistic benefits of ecosystem management on both carbon storage and water quality. The findings, therefore, reinforce the empirical basis for considering carbon sequestration and water quality not as separate outcomes but as interconnected services within predictive ecological frameworks.

The forest plot summarizing the results of this meta-analysis displays the standardized effect sizes for both carbon sequestration outcomes and water quality indicators across the included studies. Each horizontal line represents an individual study, with the central square indicating the point estimate of the effect size and the line length denoting the 95% confidence interval. Studies are grouped by ecological domain, including mangroves, salt marshes, seagrass meadows, and estuarine systems for carbon storage, and nutrient enrichment, dissolved oxygen, turbidity, and chlorophyll-a for water quality. The pooled effect size for carbon sequestration demonstrates a significantly positive outcome, with mangroves showing the largest mean effect size, followed by salt marshes and seagrasses, reflecting their strong soil organic carbon accumulation and burial potential. For water quality, pooled results show consistent associations between elevated nutrient inputs and reduced dissolved oxygen levels, while AI-based predictive models yield higher accuracy scores compared to traditional statistical models. The diamond shapes at the bottom of each subgroup indicate the overall pooled effect size, with all carbon-related outcomes falling to the right of the zero line, suggesting robust sequestration benefits, and water-quality-related models clustered around significant predictive accuracy values.

Heterogeneity statistics displayed alongside the forest plot confirm variation across studies, with I^2 values exceeding 70% in several subgroups, indicating substantial ecological and methodological diversity. Subgroup analyses are clearly visualized within the plot, showing biome-specific differences, such as the high sequestration effect sizes for Southeast Asian mangroves compared to moderate estimates in temperate systems, and greater water-quality predictability in machine learning frameworks relative to process-only models. Prediction intervals are represented, illustrating the expected range of true effects beyond the included studies, further emphasizing the broad applicability of the findings. Sensitivity tests removing high-risk studies are displayed in secondary plots, showing minimal shifts in pooled estimates, thereby reinforcing the stability of the results. Overall, the forest plot conveys a comprehensive visual synthesis of individual study effects, pooled outcomes, and subgroup variability, highlighting the reliability of predictive modeling approaches for evaluating both carbon sequestration and water quality in coastal ecosystems.

DISCUSSION

The findings of this meta-analysis confirmed that mangroves, salt marshes, and seagrass meadows serve as disproportionately important carbon sinks relative to their global area, a conclusion that aligns with earlier seminal studies of blue carbon ecosystems. Newman et al. (2019) emphasized that mangrove soils, because of their high organic matter content and persistent anoxia, store carbon densities surpassing 1,000 Mg C ha^{-1}, results echoed in this synthesis. Similarly, Thi Hang et al. (2024)

demonstrated strong sequestration rates in salt marshes, which were consistent with the robust effect sizes observed in the present analysis. In line with Frincu (2024), who reported extensive long-term carbon accumulation in seagrass soils, this review also found moderate but significant storage potential in seagrass ecosystems, particularly under conditions of improved water clarity. These findings reinforce the conclusions of Newman et al. (2019), who highlighted the biogeochemical uniqueness of coastal ecosystems in mediating carbon burial processes. However, this meta-analysis adds value by demonstrating that pooled effect sizes remain consistently positive across global contexts, even when accounting for methodological and ecological heterogeneity. Earlier work, such as Velasquez-Camacho et al.(2024), framed blue carbon primarily in a conservation and policy discourse, whereas the current synthesis underscores empirical and predictive modeling evidence, illustrating the robustness of these outcomes across diverse data sources and modeling approaches. Thus, this research situates itself within and extends the legacy of prior studies by quantifying, through a comparative lens, the relative contributions of coastal ecosystems to global carbon budgets.

The synthesis of water quality outcomes further revealed strong predictive associations between nutrient enrichment and ecological degradation, which aligns with the extensive literature on eutrophication and hypoxia. Perry et al. (2022)first articulated the mechanistic link between nitrogen and phosphorus inputs and primary production, and this relationship was further detailed by Wege et al. (2020), who documented widespread coastal hypoxia as a product of excess nutrient loading. The present analysis supported these earlier observations, showing consistent negative correlations between nutrient inputs and dissolved oxygen across global estuarine systems. The Gulf of Mexico dead zone, frequently cited in studies by Thi Hang et al.(2024), served as a benchmark case within the included studies, and results confirmed the predictive accuracy of coupled hydrodynamic–biogeochemical models in estimating hypoxic severity. Similarly, Conley et al. (2009) found comparable outcomes in the Baltic Sea, which were replicated in the pooled estimates of this meta-analysis. Studies such as Cheng et al. (2020) have highlighted the rise of harmful algal blooms under nutrient-enriched conditions, and the present synthesis validated this linkage, particularly where AI-assisted models improved bloom prediction accuracy. The novelty of these findings lies in the convergence of classical biogeochemical frameworks with machine learning–based approaches, which outperform traditional regression methods in short-term prediction of water quality metrics, a result that extends beyond the foundational insights of Wege et al. (2020). Collectively, these results corroborate earlier studies while advancing the field by demonstrating that AI-assisted predictive models can reliably capture the same nutrient–oxygen–algal dynamics observed historically but with higher temporal and spatial resolution.

A critical comparison of predictive modeling frameworks revealed that hybrid and machine learning approaches provided superior predictive performance relative to traditional process-only models, though both approaches offered unique contributions. Process-based models such as SWAT Cheng et al. (2020) and HSPF have long been the standard for watershed nutrient and pollutant transport modeling, and studies such as Perry et al. (2022)and Albahri et al. (2024)demonstrated their ability to simulate eutrophication and hypoxia dynamics. The present meta-analysis confirmed their utility, particularly in mechanistic interpretability and scenario testing, but found their predictive accuracy was often surpassed by machine learning approaches, consistent with the evaluations of (Velasquez-Camacho et al., 2024). Random forests, support vector regression, and deep neural networks achieved higher skill metrics (RMSE, AUC, R^2) in predicting water quality parameters, paralleling the findings of Selvaraj and Gallego Pérez (2023), who emphasized their capacity to handle nonlinear and high-dimensional data. Moreover, LSTM models captured temporal dynamics in dissolved oxygen and algal blooms with greater accuracy, corroborating findings reported by Velasquez-Camacho et al. (2024) and Newman et al. (2019). This review extends these earlier studies by quantitatively demonstrating, through pooled effect sizes, that AI-driven models not only replicate but also enhance the predictive skill established by process-based models, particularly in short-term operational forecasting contexts. Therefore, the results situate contemporary AI approaches as complementary, rather than substitutive, tools within ecological modeling, enhancing the predictive capacity established by earlier mechanistic frameworks.

The integrated findings on carbon sequestration and water quality reveal strong reciprocal linkages between improved water quality and enhanced carbon burial, a relationship that has been suggested in earlier ecological studies but less frequently quantified in meta-analytic form. Liu et al., (2024)and Reichstein et al. (2019)established that water clarity is essential for seagrass productivity and subsequent carbon storage, and the present analysis confirmed that improved optical conditions directly translated into higher carbon accumulation rates. Velasquez-Camacho et al., (2024) documented how nutrient enrichment in marshes alters belowground biomass allocation, influencing soil carbon sequestration, which was consistent with the observed moderator effects in this review. Similarly, studies by Reichstein et al. (2019) highlighted the sensitivity of mangrove carbon storage to water quality, particularly salinity and sulfide concentrations, results that were reproduced in the pooled analyses. The synergistic evidence presented here also resonates with Velasquez-Camacho et al.(2024), who framed coastal ecosystems as multifunctional systems delivering co-benefits of water quality regulation and carbon sequestration. What this meta-analysis contributes beyond these earlier findings is a quantitative synthesis showing that predictive models integrating water quality and carbon storage parameters consistently yield strong effect sizes, underscoring the interdependence of these processes. This reinforces prior ecological observations while situating them within a predictive modeling framework, thereby confirming empirically the linkages hypothesized by earlier research.

High heterogeneity across studies was observed in this synthesis, a finding that mirrors challenges documented in earlier ecological meta-analyses. Cheng et al. (2020)have highlighted that ecological meta-analyses are inherently heterogeneous due to differences in geography, methods, and study design. The present analysis confirmed this, with I^2 values often exceeding 70%, comparable to levels reported in other environmental reviews. Subgroup analyses revealed that biome type, geographic region, and modeling approach significantly moderated outcomes, which resonates with earlier studies by Newman et al.(2019), who emphasized geomorphic context in mangrove carbon storage, and Liu et al. (2024), who highlighted hydrodynamic differences in nutrient cycling. Furthermore, the observation that machine learning models outperformed traditional approaches in predictive skill reflects the broader trend reported in environmental data science reviews. By quantifying these moderators, this review validates prior claims while situating them in a broader comparative framework, confirming that ecological variability is both expected and explainable through stratified analysis.

The evaluation of risk of bias and publication bias revealed patterns consistent with earlier systematic reviews of ecological interventions. Smaller studies tended to report larger positive effects, echoing concerns raised by Reichstein et al. (2019), who noted the prevalence of small-study effects in ecological meta-analysis. Funnel plot asymmetry and Egger's regression indicated potential bias, but trim-and-fill procedures suggested that these biases did not substantially alter the overall pooled estimates. This is consistent with the findings of Velasquez-Camacho et al. (2024), who observed that while ecological meta-analyses often contain detectable bias, their influence on general conclusions is usually modest. Moreover, the use of robust variance estimation and sensitivity analyses to account for dependence and study quality reflects methodological best practices advocated by Coro et al. (2024). By applying these rigorous methods, this meta-analysis demonstrated that its findings remain stable even under exclusion of high-risk studies, aligning with earlier reviews such as Velasquez-Camacho et al.(2024), which emphasized the need for transparency in evaluating blue carbon systems. These comparisons reinforce the methodological reliability of the current synthesis while acknowledging limitations observed historically in the field. Finally, the integration of AI with ecological predictive frameworks in this analysis highlights an interdisciplinary advancement that extends beyond traditional ecological modeling, a trend increasingly recognized in recent reviews. Liu et al. (2025) emphasized the transformative potential of machine learning in Earth system science, and the findings here confirm that such approaches consistently outperform traditional models in predictive accuracy for both carbon sequestration and water quality outcomes. Similarly, Rajitha et al. (2024) introduced the concept of physics-guided neural networks, which combine mechanistic knowledge with machine learning, an approach validated in this review through the superior performance of hybrid models. Earlier ecological studies, such as Brasier et al. (2021)and Kennicutt et al. (2014), framed ecosystem services primarily within ecological or economic paradigms, whereas the present synthesis illustrates the computational dimension of integrating ecological and AI-based frameworks. This interdisciplinary comparison situates the current results within a broader scientific trajectory, showing that the convergence of ecological process understanding, and computational intelligence has begun to yield empirically validated outcomes. The consistency of these findings with both ecological and computational research underscores the robustness of the integrated framework and its capacity to unify historically separate strands of inquiry.

Review of Applied Science and Technology
Volume 04, Issue 02 (2025)
Page No: 669 – 696
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CONCLUSION

This meta-analysis provides a comprehensive synthesis of predictive modeling for coastal ecosystem carbon sequestration and water quality assessment, integrating evidence across ecological, biogeochemical, and computational domains. The findings confirm that blue carbon ecosystems—mangroves, salt marshes, and seagrass meadows—are consistent and significant carbon sinks, storing and burying organic matter at rates far exceeding many terrestrial systems. At the same time, water quality dynamics emerged as central determinants of sequestration outcomes, with nutrient loading, optical clarity, and oxygen dynamics shaping whether organic carbon is buried or respired. The pooled results underscore the interdependence of carbon storage and water quality regulation, validating decades of ecological research while extending it into a predictive modeling framework. The synthesis also demonstrates the methodological advances made possible by artificial intelligence and machine learning approaches. Traditional process-based models, such as hydrodynamic–biogeochemical frameworks, remain valuable for mechanistic understanding and scenario testing, yet AI-driven models consistently offered greater predictive skill, particularly for short-term forecasting of eutrophication, hypoxia, and algal bloom dynamics. The integration of AI with ecological principles not only improved predictive accuracy but also strengthened the interpretability of outputs by aligning computational predictions with established ecological processes. This hybridization reflects an important methodological evolution in environmental monitoring, bridging the gap between mechanistic realism and computational power. In addition, the analysis highlights that predictive modeling for carbon sequestration and water quality assessment is not simply a tool for academic inquiry but a framework that enables the comparison, synthesis, and validation of diverse data streams across scales and geographies. By harmonizing effect sizes, evaluating heterogeneity, and accounting for publication bias, this study provides robust, empirically grounded evidence that predictive frameworks can reliably assess and forecast ecological outcomes in coastal systems. The convergence of ecological understanding and AI-based modeling thus emerges as a validated approach for synthesizing knowledge, offering a structured foundation upon which assessments of ecosystem services can be built and rigorously evaluated.

RECOMMENDATIONS

The synthesis of evidence on coastal carbon sequestration and water quality assessment suggests that predictive modeling frameworks should be expanded through integrative and interdisciplinary applications. Ecologists, data scientists, and environmental managers should prioritize the development of hybrid models that couple mechanistic biogeochemical processes with artificial intelligence approaches such as machine learning and deep learning. These models demonstrated superior predictive skill in this meta-analysis, particularly for short-term water quality forecasting and biomass estimation, while retaining interpretability when constrained by ecological principles. Future modeling efforts should therefore incorporate process knowledge into data-driven systems to ensure both accuracy and ecological relevance, thereby improving their applicability in dynamic and heterogeneous coastal environments. In addition, comprehensive monitoring systems should be established to support predictive frameworks with high-quality data. The findings revealed that water quality dynamics, including nutrient loading, dissolved oxygen fluctuations, and optical clarity, directly influence carbon storage outcomes, underscoring the need for continuous measurements at multiple spatial and temporal scales. It is recommended that remote sensing platforms, in situ sensor networks, and long-term ecological surveys be integrated to provide the multimodal datasets required by advanced predictive models. Particular emphasis should be placed on filling geographical gaps in regions such as Africa and South America, where studies remain underrepresented despite the presence of critical blue carbon ecosystems. Expanding the scope of global datasets will allow predictive frameworks to capture variability across diverse ecological contexts and enhance the generalizability of meta-analytic findings. In addition, predictive modeling should be systematically embedded into ecosystem service assessments and management strategies. The combined evidence demonstrated strong linkages between improved water quality and enhanced carbon sequestration, suggesting that predictive frameworks can serve as decision-support tools for coastal restoration, conservation, and policy initiatives. Policymakers and practitioners are encouraged to adopt AI-integrated ecological models when designing management interventions, as these frameworks can evaluate potential outcomes with higher precision than conventional approaches. Furthermore, risk-of-bias and uncertainty assessments should be incorporated into practical applications to ensure transparency and credibility in policy-relevant predictions. By embedding predictive modeling within environmental governance, research can be translated into actionable insights that strengthen coastal resilience and enhance the long-term sustainability of blue carbon ecosystems.

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