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Integrative Assessment of Coastal Vegetation Restoration Effectiveness Using Remote Sensing, Isotopic Proxies, and Machine Learning

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ABSTRACT

Coastal ecosystems such as mangroves, salt marshes, and seagrass meadows play a central role in carbon storage, shoreline protection, and habitat provision. Restoration efforts have expanded globally, but systematic methods to evaluate their effectiveness remain limited. Field surveys provide accurate data at local scales but are restricted in coverage and continuity. This paper reviews approaches that integrate remote sensing, isotopic proxy analysis, and machine learning for assessing coastal vegetation restoration. Remote sensing enables spatial and temporal monitoring of vegetation change. Isotopic proxies provide indicators of nutrient dynamics and carbon sequestration. Machine learning supports the integration of heterogeneous datasets and the development of predictive models. The combination of these methods allows assessment of structural and functional recovery at multiple scales. A framework is outlined for applying these approaches in restoration monitoring and management. Research directions are identified in relation to sampling design, data integration, and policy applications.

Keywords: *guiding adaptive management, ensuring accountability, integrate remote sensing.*

Introduction

Coastal ecosystems, including mangroves, salt marshes, and seagrass meadows, provide essential ecological services that support biodiversity, mitigate climate change, and sustain human livelihoods. These ecosystems sequester carbon at rates significantly higher than many terrestrial forests, regulate nutrient cycles, and stabilize coastlines against erosion [1]. However, widespread anthropogenic pressures, such as coastal development, aquaculture expansion, pollution, and climate-driven sea level rise, have resulted in substantial degradation of these systems. Restoration of coastal vegetation has therefore become a global priority, with initiatives undertaken in many regions to re-establish ecological function and secure long-term ecosystem services. Despite the increasing scale of restoration projects, evaluating their effectiveness remains a methodological challenge. Conventional assessment relies heavily on field-based ecological surveys, which provide detailed measurements of vegetation structure, biomass, and species composition. While these approaches yield accurate site-specific information, they are often labor-intensive, costly, and temporally constrained, limiting their utility for monitoring large spatial extents or long-term restoration outcomes [2], restoration success is not only determined by vegetation re-establishment but also by the recovery of ecological processes such as nutrient cycling, primary productivity, and carbon sequestration, which require complementary assessment methods.

Recent advances in remote sensing technologies have created opportunities for large-scale and cost-effective monitoring of coastal vegetation restoration. Satellite platforms, airborne sensors, and unmanned aerial systems can detect changes in vegetation cover, canopy height, and spectral properties over time. For example, high-resolution multispectral and hyperspectral imagery allow identification of species composition and physiological status, while LiDAR provides three-dimensional structural information that is critical for estimating aboveground biomass [3]. Remote sensing thus provides scalable tools for assessing both structural and functional indicators of ecosystem recovery. Alongside remote sensing, isotopic proxies have emerged as valuable indicators of ecosystem processes in restored coastal environments. Stable isotopes of carbon ($\delta^{13}C$) and nitrogen ($\delta^{15}N$) can reveal sources of organic matter, trophic interactions, and nutrient dynamics, while radiocarbon dating offers insights into soil carbon accumulation and turnover rates [4]. In restoration contexts, isotopic analysis allows the evaluation of whether nutrient cycling and carbon sequestration processes in restored sites converge with those observed in natural reference systems. This approach provides a direct measure of functional recovery beyond visual vegetation growth metrics.

The increasing availability of complex datasets from remote sensing, field surveys, and isotopic analysis raises the need for advanced analytical frameworks. Machine learning offers a suite of computational approaches capable of integrating diverse data sources, detecting nonlinear patterns, and generating predictive models. Algorithms such as random forests, support vector machines, and neural networks have been applied to vegetation classification, biomass estimation, and carbon stock prediction. In restoration monitoring, machine learning can enhance accuracy by combining spectral, structural, and isotopic information, thereby producing more comprehensive assessments of ecosystem recovery trajectories [5]. An integrative approach that combines remote sensing, isotopic proxies, and machine learning can therefore provide a robust framework for evaluating coastal vegetation restoration effectiveness.

Such an approach enables assessment across multiple spatial and temporal scales, captures both structural and functional recovery, and supports predictive modeling of restoration outcomes under varying environmental conditions [6]. By bridging ecological fieldwork with advanced computational methods, this integration addresses existing limitations in restoration monitoring and improves the evidence base for management decisions.

The application of integrative monitoring approaches also has implications for policy and practice. Restoration projects are increasingly tied to international frameworks such as the United Nations Decade on Ecosystem Restoration and climate mitigation commitments under the Paris Agreement. Demonstrating restoration effectiveness through transparent, scientifically validated methods is essential for securing financial support, guiding adaptive management, and ensuring accountability. Integrating remote sensing, isotopic analysis, and machine learning provides a pathway toward standardized, reproducible, and scalable evaluation frameworks that align with these global priorities [7]. This paper reviews current progress in applying remote sensing, isotopic proxies, and machine learning for coastal vegetation restoration monitoring. It outlines the strengths and limitations of each method, describes their potential synergies, and proposes a conceptual framework for integrated assessment.

Remote Sensing Approaches for Coastal Vegetation Monitoring

Remote sensing has become a cornerstone of ecological monitoring, offering scalable, repeatable, and relatively cost-effective methods for tracking coastal vegetation dynamics. Unlike traditional field surveys, which are spatially restricted and resource-intensive, remote sensing enables systematic observation of entire coastlines over long temporal scales [8]. For coastal vegetation restoration, these approaches are particularly valuable, as they allow detection of changes in vegetation cover, canopy structure, and ecological connectivity, thereby providing indicators of restoration effectiveness.

Optical Sensors

Optical remote sensing has been widely applied to monitor vegetation condition and distribution. Satellite systems such as Landsat, Sentinel-2, and PlanetScope provide multispectral imagery that is especially useful for detecting vegetation dynamics through spectral indices. The Normalized Difference Vegetation Index (NDVI) remains the most commonly used, reflecting chlorophyll activity and photosynthetic vigor. However, indices such as the Enhanced Vegetation Index (EVI) and Soil-Adjusted Vegetation Index (SAVI) have been increasingly utilized to correct for atmospheric interference and soil background reflectance, both of which are significant in intertidal and coastal environments. Long-term data archives, particularly from Landsat, allow assessment of historical vegetation trajectories, while newer high-resolution platforms such as PlanetScope enable fine-scale monitoring of restoration plots. Optical data, however, face limitations in cloudy or rainy environments, which are frequent in coastal regions [9]. Despite these challenges, the integration of multi-temporal optical datasets has proven effective in detecting vegetation phenology, colonization patterns in restoration sites, and spatial shifts driven by sea-level rise or human interventions.

Radar and LiDAR

While optical sensors provide spectral insights, structural information is better captured through active remote sensing technologies such as Synthetic Aperture Radar (SAR) and Light Detection and Ranging (LiDAR). SAR penetrates cloud cover and can capture data regardless of lighting conditions, making it highly reliable for monitoring in tropical and subtropical coastal zones. Its backscatter signals are sensitive to vegetation structure, canopy density, and water content, which are key indicators of ecosystem recovery in mangroves and salt marshes. For instance, SAR data have been used to map mangrove biomass, monitor hydrological dynamics, and detect storm-related damages. Airborne and terrestrial LiDAR, on the other hand, provide three-dimensional representations of vegetation canopies, delivering precise measurements of canopy height, vertical structure, and aboveground biomass. In restoration projects, LiDAR has been instrumental in quantifying growth rates of replanted mangroves, detecting changes in canopy closure, and modeling habitat suitability for fauna dependent on coastal vegetation [10]. Combined SAR-LiDAR applications further enhance the ability to assess both horizontal and vertical aspects of restoration success.

Drone-Based Imaging

Unmanned Aerial Vehicles (UAVs) are increasingly being adopted in restoration monitoring due to their ability to capture ultra-high-resolution imagery at flexible temporal intervals. UAV platforms equipped with RGB, multispectral, or thermal cameras provide detailed spatial data for small to medium-scale restoration plots. Such imagery is particularly useful for assessing seedling survival, species-specific composition, and canopy density. Compared to satellite-based sensors, UAVs offer the advantage of site-specific customization and rapid deployment, making them suitable for adaptive management practices. For example, drone surveys can be aligned with planting cycles, enabling managers to assess survival immediately after planting and to monitor stress responses under variable hydrological or climatic conditions [11]. However, UAV applications are limited in spatial coverage and are best used in conjunction with broader-scale satellite data.

Quantification of Spatial Metrics

A key contribution of remote sensing is its ability to derive spatial metrics relevant to ecological restoration. Metrics such as vegetation cover, patch size distribution, connectivity, and successional trajectories can be quantified across temporal sequences. These indicators not only describe the extent of vegetation recovery but also provide insights into landscape-level processes, including habitat connectivity and resilience. In coastal ecosystems, where fragmentation reduces ecological function, such spatial metrics are critical for evaluating whether restoration interventions lead to functional recovery. Remote sensing approaches thus provide a multidimensional perspective on restoration outcomes by combining spectral, structural, and spatial analyses. Optical sensors track vegetation health, radar and LiDAR capture canopy structure and biomass, and UAVs deliver high-resolution imagery for plot-level assessments [12]. Together, these tools generate complementary datasets that support robust evaluations of restoration effectiveness across scales.

Isotopic Proxies as Functional Indicators

The evaluation of coastal vegetation restoration requires indicators that go beyond structural measures such as canopy cover or biomass. Functional recovery, particularly in terms of biogeochemical processes, is central to determining whether restored ecosystems provide services comparable to undisturbed systems. Stable and radiogenic isotopes have emerged as valuable tools in this regard, as they capture information on carbon and nitrogen cycling, organic matter sources, and long-term carbon storage [13]. By applying isotopic approaches, researchers are able to assess ecosystem function in ways that conventional monitoring methods cannot.

Carbon Isotopes ($\delta^{13}C$)

Stable carbon isotopes ($\delta^{13}C$) provide information on the sources of primary productivity and pathways of carbon assimilation within coastal ecosystems [14]. Different plant groups, such as mangroves, seagrasses, and salt marsh species, exhibit distinct $\delta^{13}C$ signatures due to differences in photosynthetic pathways and carbon source utilization. For instance, mangroves growing in intertidal environments often display enriched $\delta^{13}C$ values compared to seagrasses, reflecting variations in dissolved inorganic carbon pools. In restoration monitoring, $\delta^{13}C$ values can be used to verify whether newly planted or naturally regenerating vegetation assimilates carbon in a manner consistent with mature reference stands. Furthermore, by analyzing soil organic matter $\delta^{13}C$, researchers can infer the relative contributions of autochthonous (plant-derived) versus allochthonous (external) inputs, thereby assessing the development of ecosystem-specific carbon pools. This is particularly relevant to evaluating blue carbon sequestration potential in restored habitats.

Nitrogen Isotopes ($\delta^{15}N$)

Nitrogen isotopes ($\delta^{15}N$) serve as indicators of nutrient cycling and anthropogenic influences within coastal ecosystems. Elevated $\delta^{15}N$ values in plant tissue often signify wastewater or agricultural nutrient inputs, while lower values may indicate reliance on atmospheric or microbial nitrogen fixation. In restored mangroves or marshes, $\delta^{15}N$ patterns can reveal the extent to which ecosystems have established internal nutrient cycling processes comparable to natural reference systems. By analyzing $\delta^{15}N$ in both vegetation and sediment, researchers can evaluate microbial transformations such as denitrification, which play critical roles in nitrogen removal and water quality improvement [15]. These assessments are particularly important in urban or agricultural coastlines, where nutrient enrichment can undermine restoration success. The ability to trace anthropogenic versus natural nitrogen sources provides a functional measure of ecological resilience in restored habitats.

Radiocarbon (^{14}C)

Radiocarbon (^{14}C) analysis offers insights into the persistence and age of organic carbon stored in soils and sediments. In coastal ecosystems, where long-term carbon storage represents a significant climate mitigation service, ^{14}C data are particularly valuable. Restored sites may initially accumulate younger organic matter with shorter turnover times, while mature systems often contain older, more stabilized carbon pools.By comparing ^{14}C signatures of restored versus reference ecosystems, it is possible to evaluate the progression of soil organic matter stabilization, a key determinant of blue carbon sequestration [16]. This approach thus provides a temporal perspective, complementing short-term monitoring of vegetation growth with long-term assessments of carbon storage potential.

Functional Comparisons with Reference Ecosystems

The integration of $\delta^{13}C$, $\delta^{15}N$, and ^{14}C analyses enables researchers to move beyond simple biomass or cover-based indicators. By linking isotopic patterns with vegetation recovery, it becomes possible to determine whether restored ecosystems replicate the functional characteristics of natural systems. For example, convergence of $\delta^{13}C$ and $\delta^{15}N$ values between restored and reference stands may indicate the re-establishment of ecosystem-specific carbon and nutrient cycles. Similarly, radiocarbon evidence of increasing soil organic carbon age suggests progression toward long-term carbon sequestration comparable to undisturbed sites. Isotopic proxies thus provide robust, process-oriented indicators of restoration success [17]. Carbon isotopes track productivity and carbon source dynamics, nitrogen isotopes reveal nutrient cycling and anthropogenic inputs, and radiocarbon quantifies organic carbon persistence. Together, these tools allow for a functional evaluation of restored coastal ecosystems, ensuring that monitoring captures both ecological structure and the underlying biogeochemical processes critical to ecosystem service provision.

Table 1. Remote sensing tools and their applications in coastal vegetation monitoring

Technique	Data Source / Sensor	Application in Restoration Monitoring
Optical Sensors	Landsat, Sentinel-2, PlanetScope	Vegetation indices (NDVI, EVI, SAVI), canopy cover, phenology
Radar (SAR)	Sentinel-1, ALOS PALSAR	Biomass estimation, soil moisture, flood dynamics
LiDAR	Airborne or drone-based	Canopy height, structural complexity, above-ground biomass
UAV Imaging	Drone multispectral / RGB	High-resolution survival rates, species composition, canopy density

Table 2. Isotopic proxies used in restoration effectiveness assessment

Isotope Marker	Ecological Function Assessed	Application in Restoration Projects
δ13C (Carbon)	Source of primary productivity, carbon sequestration	Differentiates mangrove, seagrass, and terrestrial carbon pools
δ15N (Nitrogen)	Nutrient cycling, anthropogenic inputs, microbial processes	Tracks eutrophication and nutrient recovery
14C (Radiocarbon)	Soil organic carbon persistence	Blue carbon storage and long-term sequestration potential

Table 3. Machine learning approaches for restoration assessment

ML Approach	Example Algorithm	Application in Coastal Vegetation Monitoring
Classification	Random Forests, SVM	Species identification, invasive species detection, vegetation health
Regression	Gradient Boosting, CNNs	Biomass estimation, canopy density, soil carbon prediction
Predictive Modeling	Ensemble models, LSTM	Forecasting restoration outcomes under climate and management scenarios

Table 4. Proposed integrative framework for restoration assessment

Step	Data / Tools Used	Purpose in Assessment
Baseline Characterization	Isotopic proxies, high-resolution imagery	Establish pre-restoration ecological condition
Monitoring Phase	Multi-temporal satellite/drone observations	Track vegetation recovery and ecosystem dynamics
Data Integration	ML models integrating isotopic + RS data	Link structure with function, detect trends
Decision Support	Dashboards, scenario analysis	Provide managers and policymakers actionable insights

Machine Learning for Restoration Assessment

The growing availability of large and complex datasets from remote sensing platforms, isotopic measurements, and field surveys has created opportunities for advanced analytical approaches in ecological restoration monitoring. Traditional statistical methods often struggle to capture the non-linear relationships and multidimensional interactions that characterize coastal ecosystems. Machine learning (ML) algorithms, by contrast, offer a flexible framework for pattern recognition, prediction, and data integration. When applied to restoration assessment, ML enhances both the accuracy and efficiency of monitoring efforts, providing insights that support adaptive management.

One important application of ML lies in classification tasks. Algorithms such as Random Forests and Support Vector Machines have demonstrated strong performance in identifying plant species, detecting invasive taxa, and assessing vegetation health using remote sensing imagery [18]. These models can process spectral signatures from satellites or drones and assign them to specific vegetation types with high precision. In restoration contexts, this allows managers to track species composition over time, evaluate the survival of planted individuals, and identify areas where invasive species may threaten project success, regression-based models are valuable for quantifying structural and functional attributes of restored ecosystems. Gradient boosting techniques and deep learning models can estimate biomass, canopy density, and even soil carbon stocks by linking spectral and isotopic inputs to field measurements. These estimates provide continuous and spatially explicit data layers, reducing the need for intensive field sampling. By incorporating isotopic proxies such as $\delta^{13}C$ or $\delta^{15}N$ into regression models, it is possible to couple vegetation structure with functional indicators, yielding a more holistic picture of ecosystem recovery. Predictive modeling represents another frontier for ML applications [4]. By integrating long-term datasets with current monitoring inputs, algorithms can forecast restoration trajectories under varying climate conditions and management strategies. For example, ML can simulate how sea-level rise or nutrient enrichment might influence vegetation dynamics, thereby guiding proactive interventions. Such forecasting capacity is particularly valuable in coastal regions, where restoration outcomes are highly sensitive to environmental change [8]. The integration of ML with remote sensing and isotopic data thus strengthens the predictive and diagnostic capacity of restoration science. By combining structural indicators from imagery with functional insights from isotopes, ML creates a unified framework for evaluating both ecosystem condition and trajectory. This integration supports evidence-based management, allowing practitioners to make informed decisions that improve restoration outcomes and enhance the long-term resilience of coastal ecosystems.

An Integrative Framework

Developing an effective framework for assessing coastal vegetation restoration requires combining structural, functional, and predictive indicators into a unified system. Such an approach ensures that monitoring extends beyond simple measurements of vegetation cover and instead captures the ecological processes that determine long-term restoration success. By integrating remote sensing, isotopic proxies, and machine learning, the framework supports both scientific evaluation and practical decision-making for managers and policymakers. The first step involves baseline characterization, which establishes reference conditions against which restoration progress can be evaluated. High-resolution imagery from satellites or drones provides spatial data on vegetation extent, canopy density, and landscape configuration prior to intervention [9]. At the same time, isotopic proxies such as $\delta^{13}C$, $\delta^{15}N$, and radiocarbon (^{14}C) offer functional insights into carbon sequestration, nutrient cycling, and soil organic matter stability. Together, these datasets provide a comprehensive picture of the structural and biogeochemical state of the ecosystem before restoration activities begin.

During the monitoring phase, multi-temporal observations allow for the detection of changes over time. Remote sensing platforms enable repeated assessments of vegetation cover, species composition, and successional dynamics, while isotopic measurements provide indicators of shifts in productivity and nutrient pathways. Linking temporal changes in isotopic signatures with vegetation dynamics helps determine whether restored ecosystems are converging toward natural reference systems in both structure and function. The third component is data integration, where machine learning algorithms combine spatial, functional, and contextual data. Remote sensing outputs provide information on vegetation structure, isotopes highlight ecological processes, and contextual data include hydrological conditions, management practices, and disturbance regimes. Machine learning models can synthesize these diverse datasets, identify complex interactions, and generate reliable predictions of ecosystem trajectories [12]. This integration transforms isolated datasets into a cohesive monitoring system capable of diagnosing restoration outcomes at multiple scales, the framework emphasizes decision support, translating scientific outputs into actionable tools for managers and policymakers. Predictive dashboards, built on machine learning models, can display real-time indicators of restoration effectiveness and simulate potential outcomes under different management or climate scenarios [14]. These tools provide a transparent basis for adaptive strategies, enabling stakeholders to respond quickly to emerging challenges and optimize restoration investments, baseline assessment, continuous monitoring, integrated analysis, and decision support, this framework provides a comprehensive approach to evaluating coastal vegetation restoration. It bridges the gap between research and practice, ensuring that scientific insights directly inform adaptive management and policy development.

Research Priorities

Future research on coastal vegetation restoration should focus on advancing methodologies that improve both the scalability and applicability of monitoring frameworks. A key priority is the development of low-cost isotopic sampling protocols suitable for large-scale restoration initiatives.

While isotopic analyses provide valuable insights into ecosystem function, the associated costs and logistical demands often restrict their application to small-scale studies. Simplified sampling approaches, field-ready tools, and standardized protocols would enable wider use of isotopic proxies, particularly in resource-limited contexts. Another important direction is improving machine learning interpretability in ecological applications. Many ML models, particularly deep learning approaches, are often viewed as “black boxes,” limiting stakeholder trust and adoption. Research should prioritize developing interpretable algorithms and visualization tools that clearly explain how models derive predictions [16]. Such transparency is essential to ensure that outputs are both scientifically credible and usable by practitioners making restoration decisions.

The integration of socio-ecological dimensions into monitoring frameworks also requires attention. Restoration success is not solely determined by ecological metrics but is strongly influenced by human engagement, governance structures, and cultural practices [9]. Future studies should combine remote sensing and ML-based monitoring with participatory approaches that include local community perspectives. This integration would ensure that restoration projects are both ecologically effective and socially sustainable, there is a need for harmonization of international monitoring standards for coastal ecosystem restoration. Current practices vary widely across regions, hindering the ability to compare outcomes or synthesize global trends. Developing common guidelines for data collection, isotopic analysis, and remote sensing interpretation would enhance comparability, facilitate cross-site learning, and support global assessments of restoration progress, these research priorities aim to strengthen the scientific basis of restoration monitoring while ensuring that methods are practical, transparent, and globally relevant.

Conclusion

The assessment of coastal vegetation restoration requires approaches that move beyond traditional ecological surveys. Conventional monitoring captures limited aspects of ecosystem recovery and often fails to link structural observations with underlying functional processes, remote sensing, isotopic proxies, and machine learning, restoration outcomes can be evaluated in a more comprehensive and scalable manner. Remote sensing contributes spatially explicit information on vegetation cover and dynamics, isotopic proxies provide insights into nutrient cycling and carbon sequestration, while machine learning facilitates data integration and predictive modeling. Together, these tools offer an interdisciplinary framework that captures both ecological function and resilience. Importantly, such integration also supports decision-making by providing managers and policymakers with evidence-based tools to evaluate progress and adapt strategies. In an era of accelerating global change, this combined approach offers a robust pathway to ensure the long-term effectiveness of coastal ecosystem restoration initiatives.

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