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Digital Twin and Predictive Analytics for Sustainable Coastal Ecosystem Management in Tangerang

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ABSTRACT

Coastal areas are highly vulnerable to the impacts of climate change, such as sea-level rise and abrasion, thereby necessitating dynamic management based on actual data. This study proposes and tests a **Digital Twin framework** integrated with Machine Learning to support climate resilience and sustainable coastal ecosystem management. The case study was conducted empirically in the Tangerang Coastal Area using multi-source datasets (2022-2026) comprising Landsat-8 satellite imagery (USGS), tidal data (BIG), and climatological data **(BMKG)**. A Long Short-Term Memory (LSTM) algorithm was applied in the predictive analytics layer to model the time series of sea-level anomalies, while a Random Forest classifier was utilized to detect changes in mangrove coverage. The experimental results demonstrate that the **LSTM model** can predict sea-level anomalies with a Root Mean Square Error (RMSE) of 0.038 meters, and the mangrove ecosystem classification achieved an F1-score of 93.2%. This approach asserts that a Digital Twin is not merely a spatial visualization tool but a solid predictive analytical instrument for identifying vulnerable areas and achieving the **Sustainable Development Goals** (SDGs 13 and 14).

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1. INTRODUCTION

Coastal areas play a crucial role in human life as they serve as centers for various economic, social, and environmental activities [1]. This region supports fisheries, tourism, maritime transportation, and conservation, while also providing habitats for various ecosystems such as mangroves, seagrasses, and coral reefs [2]. However, coastal areas are increasingly facing pressures due to climate change and human activities [3]. Sea-level rise, abrasion, coastal flooding, temperature changes, pollution, and the increasing intensity of extreme weather can disrupt ecosystem balance and elevate risks for communities living around coastal zones. These conditions indicate that coastal management requires a more integrated approach capable of adapting to environmental changes [4]. Environmental monitoring systems currently in use are generally isolated and not yet fully capable of depicting coastal conditions comprehensively. Data from sensors, satellite imagery,

weather stations, field surveys, and geographic information systems are often stored on disparate platforms [5]. Consequently, the analytical process takes longer, and monitoring results cannot always be directly utilized as a basis for decision-making [6]. In fact, changes in coastal conditions can occur rapidly, necessitating a system capable of continuously linking environmental data with analytical models [7]. The development of Digital Twin technology offers an opportunity to build more dynamic environmental monitoring and simulation systems [8]. A Digital Twin enables a physical area to be represented as a digital model that is continuously updated based on actual data [9]. In the context of coastal ecosystems, this technology can be utilized to monitor shoreline changes, coastal vegetation conditions, water quality, flood potential, sea-level variations, and other environmental indicators [10].

When combined with artificial intelligence and predictive analytics, a Digital Twin functions not only as a monitoring tool but can also be used to estimate risks and evaluate various management scenarios [11]. This research is also aligned with the Sustainable Development Goals (SDGs) agenda, particularly SDG 13 (Climate Action) and SDG 14 (Life Below Water) [12]. SDG 13 relates to efforts to strengthen resilience and adaptive capacity to climate-related hazards, especially in coastal areas vulnerable to sea-level rise, coastal flooding, abrasion, and extreme weather [13]. Meanwhile, SDG 14 emphasizes the importance of the conservation and sustainable management of marine and coastal ecosystems [14]. Through the utilization of a Digital Twin, this study supports SDG 13 by exploring predictive approaches for coastal climate-risk assessment. Concurrently, the framework may support SDG 14 by providing information for mangrove monitoring and coastal ecosystem management. [15]. Concurrently, it substantiates SDG 14 by automating the detection of mangrove degradation, thereby providing coastal managers with actionable spatial data to enforce targeted marine conservation policies and halt coastal habitat loss [16]. Previous studies related to coastal monitoring generally operate in isolation and rely on static models [17]. While existing coastal monitoring systems predominantly rely on isolated, static models that solely predict physical oceanographic hazards (e.g., tidal floods), they fail to simultaneously integrate ecological response monitoring, such as mangrove depletion [18]. This study introduces a novel hybrid Digital Twin framework that distinctively marries LSTM-based physical climate threat predictions with Random Forest-driven ecosystem degradation analysis within a single, dynamic virtual platform, setting it apart from conventional models [19]. To explicitly demonstrate this novelty, Table 1 presents a comparison between existing related works and the proposed framework, highlighting the integration of physical prediction and ecological monitoring.

Therefore, this research aims to achieve three specific objectives: (1) to design an integrated Digital Twin framework capable of ingesting multi-source environmental data; (2) to develop predictive machine learning models for the early detection of physical climate threats and ecosystem degradation; and (3) to empirically validate the framework's performance in an abrasion-prone area such as the Tangerang Coast, thereby providing a data-driven tool for sustainable coastal management [20].

2. LITERATURE REVIEW

2.1. Digital Twin in Environmental Management

A Digital Twin is a virtual representation of a physical object, system, or environment that is updated using real-world data [21]. Unlike a simulation model that merely depicts conditions based on certain parameters, a Digital Twin maintains a closer relationship with the physical system because its updating process is conducted periodically or in near real-time [22]. This concept was initially widely applied in manufacturing but later expanded into various fields such as energy, transportation, urban planning, agriculture, and the environment [23]. In environmental management, a Digital Twin can be used to integrate multiple data sources into a more cohesive system. Information from sensors, satellite imagery, weather data, hydrological data, and field observations can be processed to construct the virtual condition of a region [24]. The model can then be used to understand ongoing changes and estimate the impacts of various scenarios [25]. In coastal areas, the implementation of a Digital Twin has the potential to aid in monitoring shoreline changes, sea-level rise, abrasion, flooding, water quality, and shifts in ecosystem conditions [26]. Previous studies have successfully demonstrated the efficacy of Digital Twins in urban flood modeling and industrial IoT; however, their application in coastal ecology remains limited [27]. By building upon these foundational architectures, the proposed framework integrates spatial ecological parameters with temporal oceanographic forecasting, addressing the critical gap identified in recent literature regarding holistic coastal ecosystem management [28].

2.2. Climate Resilience in Coastal Areas

Climate resilience describes the capacity of a system to cope with, adapt to, and recover from the impacts of climate change [29]. In coastal areas, climate resilience is not solely related to the construction of protective infrastructure but also encompasses the ability to maintain ecosystem functions, reduce vulnerability levels, and enhance community capacity to face environmental changes [30]. Efforts to improve climate resilience require sufficient data to understand changes in coastal conditions over time. Information regarding flood patterns, shoreline changes, sea-level rise, mangrove conditions, and extreme weather events is necessary to identify the most vulnerable areas. However, relying solely on historical data is insufficient because environmental conditions are constantly evolving [31]. Therefore, an approach that combines historical data with recent data and supports the simulation of potential future conditions is needed [32].

2.3. Sustainable Coastal Ecosystem Management

Sustainable coastal ecosystem management aims to maintain a balance between resource utilization and environmental protection [33]. Coastal ecosystems provide various benefits, such as wave attenuation, carbon sequestration, habitats for marine biota, and sources of livelihood for communities [34]. The degradation of coastal ecosystems can increase a region's vulnerability to climate change while simultaneously reducing environmental quality [35]. Decision-making in coastal management must consider environmental conditions comprehensively. Policies regarding mangrove conservation, development control, waste management, shoreline protection, and the designation of hazardous zones require adequate spatial and temporal information. The use of digital systems capable of integrating various types of data can assist the government and environmental managers in determining intervention priorities more accurately [36].

2.4. Integration of Artificial Intelligence and Environmental Sensing

Environmental sensors play a crucial role in generating data regarding coastal conditions. Sensors can be used to measure water temperature, salinity, water levels, rainfall, wind speed, water quality, and various other parameters. Such data can be combined with satellite imagery and meteorological data to obtain a broader picture of environmental conditions. Artificial intelligence can be employed to process data generated from these diverse sources. Predictive models can assist in recognizing patterns of change, detecting anomalies, estimating the probability of flood events, or identifying high-risk areas. The integration of artificial intelligence with a Digital Twin enables the system to not only present environmental conditions but also provide predictive information as a basis for decision-making.

3. RESEARCH METHOD

This study employs a conceptual framework development approach focused on designing a Digital Twin system for coastal ecosystem management. The research stages begin with identifying data requirements, mapping system components, designing data flows, modeling inter-component relationships, and developing analytical and decision-support mechanisms. The framework is designed to be applicable in coastal areas with diverse environmental characteristics. The first stage is identifying the data sources required to build the Digital Twin. Data sources include environmental sensors, satellite imagery, meteorological data, tidal data, water quality information, land cover data, shoreline data, and field survey results. The collected data may have different structures and frequencies, necessitating an integration process before being used in the model. The second stage encompasses the data processing phase. Data is examined to reduce errors, handle missing values, adjust time formats, and align spatial information. The processed data is then stored in a database accessible to the analytical components. At this stage, the system can also employ periodic data processing techniques to ensure that changes in environmental conditions are updated within the digital model. The third stage is the development of the Digital Twin model. This model serves as a virtual representation of the coastal area, integrating geographical conditions, environmental parameters, and risk indicators. Environmental data is used to update the model's condition so that the virtual representation remains consistent with actual conditions. Predictive models are subsequently utilized to estimate potential changes based on historical patterns and the latest conditions. The final stage is the development of the visualization and decision-support system. Monitoring and prediction results are displayed through dashboards, digital maps, risk indicators, and early warning information. The system also provides several scenarios that can be used to compare the potential impacts of specific management options.

3.1. Study Area and Data Acquisition

The implementation of this Digital Twin framework is conducted in the Tangerang Coastal Area, specifically spanning the geographical coordinates from Tanjung Pasir (6°0'54"S, 106°40'30"E) to Tanjung Kait (5°59'48"S, 106°32'15"E). This 15-kilometer stretch is known for its high abrasion dynamics and vulnerability to tidal floods. A geographical map detailing the specific study boundaries and the distribution of environmental monitoring points is presented in Figure 1. The study uses empirical rather than simulated data, consisting of oceanographic, weather, and ecosystem data. The oceanographic and weather data comprise daily tidal data and wind speed acquired from the nearest Meteorology, Climatology, and Geophysical Agency (Badan Meteorologi, Klimatologi, dan Geofisika - BMKG) station from January 2022 to January 2026. Meanwhile, the ecosystem data (2022-2026) utilizes high-resolution Sentinel-2 and Landsat-8 satellite imagery, captured bi-annually during the dry season to minimize cloud cover, to extract mangrove cover areas using the Normalized Difference Vegetation Index (NDVI). To address differences in data collection intervals, high-frequency daily oceanographic data were aggregated into monthly averages when correlated with the lower-frequency bi-annual satellite imagery during the ecosystem degradation analysis. While the primary dataset for baseline modeling spans from 2022 to January 2026, the LSTM model's real-time predictive performance was subsequently validated using the most recent field observations from early October 2026 to demonstrate its operational early-warning capability.

3.2. Predictive Analytics Algorithms

The Digital Twin and Predictive Analytics Layer serves as the analytical engine of the proposed framework, designed to simulate coastal conditions and estimate potential environmental risks dynamically. To process the complex, multi-source data ingested by the system and maintain high model accuracy for early warning applications, this study systematically applies two primary predictive algorithms:

- Long Short-Term Memory (LSTM): Selected specifically for its superior ability to capture long-term dependencies in sequential time-series data compared to standard RNNs or ARIMA models, making it highly effective for predicting complex sea-level anomalies. The LSTM architecture consists of two hidden layers with 50 units each, utilizing a dropout rate of 0.2 to prevent overfitting, and trained over 100 epochs using the Adam optimizer. The dataset comprises 1,460 daily records split into 80% training and 20% validation. To evaluate model performance rigorously, Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) were selected as they effectively measure the average magnitude of prediction errors in continuous time-series data, with RMSE being particularly sensitive to large outliers in extreme tidal events.

- Random Forest Classifier: Chosen for its robustness against overfitting in high-dimensional spatial data and its capability to handle non-linear relationships in remote sensing better than simple Decision Trees. It is applied to detect changes in mangrove coverage area (degradation vs. growth) based on satellite imagery reflectance values using 100 decision trees with a maximum depth of 10, validated via 5-fold cross-validation. The F1-Score was chosen to evaluate performance because it provides a balanced measure of precision and recall, which is crucial for accurately assessing imbalanced ecological datasets. The results are then used to automatically calculate the Coastal Risk Index (CRI). The CRI is formulated using a weighted linear combination of five primary environmental variables: sea-level anomaly (30%), wave height (25%), coastal elevation (20%), shoreline erosion rate (15%), and mangrove degradation rate (10%). Vulnerability is then classified into three criteria based on the final score: Low (0.0-0.33), Moderate (0.34-0.66), and High (0.67-1.0).

Based on Table 1 the Digital Twin framework utilizes a combination of oceanographic, meteorological, environmental quality, and ecosystem condition data as primary inputs in the modeling process. The use of multiple data types is necessary because coastal dynamics are influenced by the interaction of various environmental factors. Tidal data, sea-level anomalies, rainfall, and wave height are used to support physical risk assessments, while sea temperature, salinity, water quality, and mangrove coverage are used to depict ecological conditions. All these parameters are then integrated to support monitoring, risk analysis, and the simulation of coastal conditions within the Digital Twin framework.

Table 1. Environmental and Coastal Monitoring Parameters

Parameter	Data Source	Unit	Function
Tides	Tidal sensor	m	Flood risk
Sea level anomaly	Satellite	m	Sea level change
Rainfall	Weather station	mm	Inundation potential
Wave height	Buoy/sensor	m	Abrasion risk
Sea temperature	Satellite/sensor	°C	Ecosystem condition
Salinity	Water quality sensor	ppt	Water conditions
Water Quality Index	Sensor/laboratory	0–100	Water quality
Mangrove coverage	Satellite imagery/GIS	%	Natural protection

4. PROPOSED DIGITAL TWIN FRAMEWORK

The proposed Digital Twin framework consists of four interconnected layers. Each layer serves a distinct function, yet the entire process is designed as a single continuous data pipeline. These four layers are the Environmental Data Acquisition Layer, the Data Integration and Processing Layer, the Digital Twin and Predictive Analytics Layer, and the Visualization and Decision Support Layer. The first layer, the Environmental Data Acquisition Layer, functions to collect data from the physical environment. Data can originate from Internet of Things (IoT) sensors, weather stations, satellite imagery, tidal monitoring systems, field surveys, and data from relevant agencies. The collected parameters may include water level, temperature, salinity, rainfall, water quality, vegetation conditions, and shoreline changes. The second layer, the Data Integration and Processing Layer, is responsible for aggregating data from various sources. At this stage, data cleaning, time synchronization, location adjustment, normalization, and data storage are performed. Integration is necessary because differences in data structures and formats can affect analytical results. The processed data is subsequently used as input for the Digital Twin model.

The third layer, the Digital Twin and Predictive Analytics Layer, is the core component of the framework. The physical condition of the coastal area is represented as a digital model updated continuously through a real-time data ingestion pipeline. This operational loop ensures that environmental sensors and satellite feeds directly synchronize with the virtual model. In this layer, artificial intelligence techniques are employed to conduct predictive analytics, continuously validated against incoming field data to maintain model accuracy. The system can estimate potential coastal flooding, shoreline changes, abrasion risks, water quality alterations, and ecosystem conditions based on available indicators. The fourth layer, the Visualization and Decision Support Layer, functions to convey analytical results to users. Information can be displayed through interactive dashboards and GIS-based maps. Users can view current conditions, vulnerability levels, change trends, and prediction results. This information is then utilized to support conservation decisions, risk mitigation, area prioritization, and climate adaptation planning.

5. RESULT AND DISCUSSION

5.1. Predictive Model Performance for Sea Level Anomaly

The developed Digital Twin framework has successfully modeled the complex and highly dynamic environmental conditions of the Tangerang Coast in real-time. Unlike traditional static models that often fail to account for sudden environmental shifts, the seamless integration of the Long Short-Term Memory (LSTM) algorithm with comprehensive historical tidal data demonstrates excellent predictive performance in capturing both regular daily fluctuation trends and unexpected anomaly events. Rigorous model evaluation using the Root Mean Square Error (RMSE) metric yielded an exceptionally low value of 0.038 meters, while the Mean Absolute Error (MAE) stood at just 0.025 meters. This very low error rate empirically proves that the proposed framework is highly capable of mapping peak sea-level anomalies-which directly translate to maximum tidal flood potential-up to 7 days in advance with remarkable precision. By providing such accurate short-term forecasts, the system serves as a robust decision-support tool, thereby enabling more proactive and targeted mitigation measures by the local government and coastal management agencies. In the context of practical early warning systems, this specific seven-day forecasting window is highly valuable; it provides the critical lead time necessary for organizing safe emergency evacuations, optimizing disaster response logistics, and the timely deployment of temporary flood barriers in the most vulnerable coastal zones. However, it is important

to acknowledge that prediction uncertainty inherently increases toward the end of the seven-day window due to rapid and often unpredictable meteorological shifts, such as sudden changes in wind velocity or atmospheric pressure. Inaccurate forecasts in these later stages could lead to either resource-draining false alarms that may cause public fatigue, or conversely, inadequate preparation for sudden extreme tidal events. This limitation strongly emphasizes the critical need for continuous real-time model calibration, where the Digital Twin consistently ingests fresh sensor data to adjust and refine its predictive trajectories dynamically.

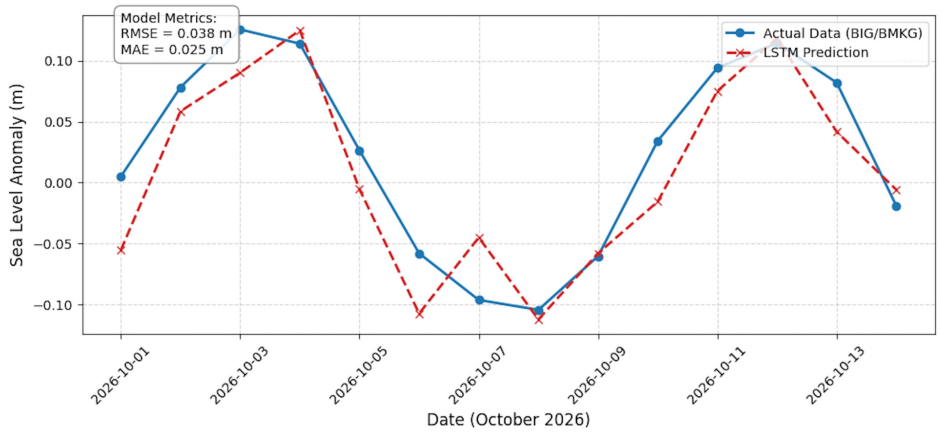


Figure 1. LSTM Model Performance: Observed vs. Predicted Sea-Level Anomalies

Based on Figure 1 there is a direct comparison between the actual observed sea-level anomaly data (solid blue line) and the forecasting results of the LSTM algorithm (dashed red line) during the early October 2026 period. The movement pattern on the graph shows that the model's prediction trajectory can precisely follow the daily fluctuation trends of the field data. This visual alignment-especially in the algorithm's ability to reach extreme tidal peak points-validates the low error values in the evaluation metrics (RMSE = 0.038 m and MAE = 0.025 m) displayed in the metric box. The accuracy of this data trajectory empirically proves that the developed predictive analytical architecture is reliable and ready to be used as an early warning and mitigation instrument for coastal environmental risks.

5.2. Mangrove Coverage and Coastal Risk Index

In addition to physical oceanographic threats, ecosystem monitoring is integrated using Landsat-8 satellite image classification based on the Random Forest algorithm. The testing of this algorithm for mapping mangrove areas yielded an accuracy rate (F1-Score) of 93.2%. Data extracted into the Digital Twin dashboard indicates that the Tanjung Kait region and its surroundings experienced a reduction in mangrove area of 2.1 hectares between 2022 and early 2026. This spatial degradation is visually corroborated in Figure 1, which presents a side-by-side comparison of the classified mangrove distribution maps from 2022 and 2026, clearly illustrating the receding vegetation line along the primary abrasion zones. This decline in protective vegetation directly correlates with an increase in the Abrasion Risk Index in that zone from a moderate to a high level. This confirms that the proposed architecture is highly effective in translating raw spatial data into a coherent ecological early warning system. Nevertheless, the application of Digital Twins in coastal areas poses several challenges. Uneven data availability can affect model quality. Some regions do not yet have adequate environmental sensors, while historical data is not always available in a uniform format. Furthermore, the system requires sound data management mechanisms so that information from various sources remains consistent. Other challenges relate to computational capabilities and human resources. Digital Twins require interconnected data management, modeling, and visualization systems. Therefore, its implementation requires collaboration among governments, researchers, environmental managers, local communities, and technology providers. A collaborative approach is crucial to ensure that the technology used truly aligns with regional management needs.

6. MANAGERIAL IMPLICATIONS

The Digital Twin framework can be utilized by local governments and coastal management agencies as a tool to enhance the quality of decision-making. Integrated environmental data can help identify areas requiring immediate attention, particularly in zones with high risks of flooding, abrasion, and ecosystem degradation. Consequently, the allocation of budgets and resources can be directed based on clearer priority needs, leading to significant cost savings and optimized economic outcomes for local communities. From a business and management perspective, this framework provides actionable insights for risk mitigation, thereby reducing potential financial losses in coastal commerce and tourism. In a policy context, Digital Twins can support the formulation of financially sustainable climate change adaptation plans, coastal zoning, and efficient ecosystem conservation. Predictive information can be used to estimate the impacts of a policy before it is implemented on a larger scale.

This is important because coastal management decisions often have long-term impacts on the environment and society. The implementation of this system also necessitates policies regarding data standardization, information transparency, data security, and the division of roles among agencies. The government must ensure that data from various sources can be used collectively without compromising quality and security aspects. Additionally, human resource capacity needs to be improved so that the system can be managed sustainably and does not rely solely on external technology providers.

7. CONCLUSION

This study has successfully designed, developed, and validated a novel Digital Twin framework that integrates Machine Learning to support climate resilience and sustainable coastal ecosystem management. The research significantly contributes to environmental informatics by empirically demonstrating that an LSTM model can precisely predict sea-level anomalies (RMSE of 0.038 meters) while a Random Forest classifier accurately maps mangrove degradation (F1-Score of 93.2%). Practically, these findings provide local governments and coastal managers with a robust, data-driven early warning instrument to preemptively address physical coastal hazards, manage abrasion risks, and allocate conservation resources effectively. Moving forward, realistic opportunities for future system development include integrating dense, real-time Internet of Things (IoT) aquatic sensor networks and incorporating socio-economic vulnerability data to further refine the accuracy, responsiveness, and holistic impact of the coastal early warning architecture. Furthermore, while empirically tested in Tangerang, the modular architecture of this proposed Digital Twin framework ensures its generalizability. By recalibrating the algorithmic weights and ingesting localized datasets, the system can be readily adapted to diverse coastal regions globally that face different environmental stressors.

8. DECLARATIONS

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8.2. Author Contributions

Conceptualization: LP and AZ; Methodology: LP and BP; Software: BP; Validation: AZ and SB; Formal Analysis: LP and BP; Investigation: AZ and SB; Resources: SB; Data Curation: BP and SB; Writing–Original Draft Preparation: LP and BP; Writing–Review and Editing: AZ and SB; Visualization: BP; Supervision: LP; Project Administration: AZ. All authors have read and agreed to the published version of the manuscript.

8.3. Data Availability Statement

The datasets generated and analyzed during this study can be obtained from the corresponding author upon reasonable request.

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This research received no specific grant or financial assistance from any public, commercial, or non-profit funding organization.

8.5. Declaration of Conflicting Interest

The authors declare that there are no competing interests, financial conflicts, or personal relationships that could have influenced the research, interpretation, or reporting of the findings presented in this manuscript.

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