Data-Driven Weighting for Coastal Vulnerability Assessment in Small Island Developing States

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***Abstract*—Coastal regions of Small Island Developing States (SIDS) face mounting risks from sea-level rise, storm surge, wave action and socio-economic pressure. Traditional vulnerability indices typically employ fixed, expert-defined weights for hazard and exposure layers, which may not adequately reflect local conditions, especially in SIDS where data scarcity and environmental variability are prevalent. This can lead to a misrepresentation of effectiveness of solutions for reducing vulnerability, particularly nature based ones that play a crucial role in these contexts. We propose a data-driven framework that leverages feature importance values derived from an XGBoost model to assign objective weights to geological and ecological features. The model was trained to predict significant wave height, and the resulting feature importance values illustrate a data-driven weighting approach that can enhance the design and refinement of coastal vulnerability indices. In addition, Shapley Additive Explanations (SHAP) values were also computed to gain deeper insights into the marginal contribution of each predictor and to validate the robustness of the feature importance results. This framework provides a way to capture the relative influence of key factors, improve the representation of nature-based solutions and support more informed adaptation planning in many countries especially SIDS.**

***Index Terms*—Regression, Machine Learning, Coastal Resilience, Artificial Intelligence**

I. Introduction

Coastal zones support a large and growing share of the world's population, infrastructure, and economic activity, with more than 600 million people currently living in low-lying coastal areas and projections exceeding one billion by 2050 [1], [2]. These regions are highly exposed to hazards such as sea level rise, tropical storms, and wave driven erosion. Small island developing states (SIDS) are especially vulnerable: limited land area, low elevations, and reliance on climate-sensitive ecosystems intensify both physical and socio-economic risks. This disproportionate vulnerability is further emphasized by resource constraints and data scarcity, which limit the capacity for detailed hazard assessments and evidence-based adaptation planning [3], [4]. Thus, Jamaica was chosen as the base country for this study, providing a practical starting point for building a broader Caribbean SIDS framework. Jamaica combines high levels of coastal exposure with comparatively greater availability of ecological, wave, and socio-economic datasets, making it a suitable case study for developing and testing a data-driven methodology that can later be extended across the region.

Composite vulnerability indices have been widely used to inform adaptation by combining multiple hazard, exposure, and ecological indicators into a single score [5], [6]. However, most existing indices assign fixed weights to these layers based on expert judgment or uniform assumptions. While practical, such approaches can misrepresent the true drivers of vulnerability, obscure the role of ecological buffers, and hinder meaningful comparisons between regions. In particular, they risk undervaluing the protective benefits of nature-based solutions (NBS) such as mangroves and coral reefs, which play a critical role in reducing coastal flooding and storm surge impacts [7].

Machine learning offers a powerful alternative by enabling data-driven estimation of the relative contributions of individual factors to observed impacts. By training models on historical hazard and impact data, feature importances derived from ensemble learners such as XGBoost [8] can serve as empirically grounded weights, reducing subjectivity and ensuring that indices more accurately reflect local conditions. Moreover, SHAP value analysis enhances interpretability by identifying which ecological and geomorphic predictors contribute most to wave height reduction, thereby quantifying the protective role of NBS in a transparent way [9]. This addresses the critique that machine learning models function as black boxes, and instead provides clear, reproducible insights for policy and planning.

In this work, we apply this framework to Jamaica, integrating geological and ecological datasets alongside historical records of coastal hazard impacts. The resulting feature-importance-driven index highlights high-risk coastal zones with greater precision than traditional equal-weight schemes. Our approach provides a transparent, reproducible, and context-sensitive tool for assessing vulnerability in SIDS, with broad applicability to other regions seeking to evaluate and enhance the role of nature-based solutions in coastal flood mitigation.

II. Related Work and Contributions

This section summarizes prior research on coastal vulnerability indices, the protective role of coastal ecosystems, and data-driven methods for assessing nature-based coastal protection.

The Comparative Coastal Risk Index (CCRI) was developed as a multidisciplinary tool to evaluate hazards and vulnerabilities across Latin America and the Caribbean. Its aim was to bring together hazard exposure, socio-economic vulnerability,

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and adaptive capacity into a single framework that could be used for regional comparison. The analysis highlighted distinct hotspots of coastal risk, offering a broad picture of where impacts are most severe. At the same time, the authors noted that the equal-weighted aggregation used in the initial application simplified complex interactions and could not fully capture the influence of factors such as ecological buffers or local geomorphology [10].

Toolkits designed for Caribbean coastal and fishing communities, such as those developed by [11], take a participatory approach to vulnerability assessment. They provide practical guidance to local stakeholders on how to document hazards, livelihoods, and ecosystem services through community-led data collection. A key insight from this work is that resilience is closely tied to the condition and distribution of ecosystems, and that assessments should account for ecosystem health, proximity to assets, and the degree of ecological protection.

Reviews of numerical and data-driven modelling in coastal and hydraulic engineering have examined how advanced computational techniques can complement or replace process-based models. This body of work describes applications of ensemble machine-learning methods, surrogate models, and hybrid approaches that combine physical process understanding with data-driven learning. The findings show that such approaches can capture nonlinear relationships between waves, bathymetry, and boundary conditions, while also providing faster and more efficient assessments than purely physics-based models [12].

More recently, [13] proposed a block-level, data-driven framework for coastal flood risk assessment that introduced fine spatial resolution into vulnerability analysis. By moving beyond coarse, regional indices, the study was able to capture local variations in exposure and vulnerability. The results demonstrated that using block-level data reveals patterns of risk that broader assessments often overlook, making it possible to design more targeted adaptation measures.

Our contributions include integrating high-resolution wave, bathymetry, mangrove, and coral reef datasets with ensemble machine-learning models. Feature importances and SHAP values are applied to construct a transparent, data-driven vulnerability index, providing a robust foundation for evidence-based coastal resilience planning.

III. Proposed Approach

A. Datasets

The datasets used are summarized in Table I, combining physical and ecological layers that provide a comprehensive basis for assessing coastal vulnerability.

B. Data Processing

We first standardized the Copernicus Marine Environment Monitoring Service (CMEMS) global wave reanalysis by selecting a single reference field to define grid dimensions and ensuring a consistent spatio-temporal structure across variables. For each spatial cell and time step, we retained significant wave height, mean wave direction, mean wave period, peak wave period, sea surface temperature, sea level anomaly, and near-surface wind speed, along with the primary swell and wind-sea partitions (swell height, mean period, peak period, and mean direction; wind-sea height, mean period, peak period, and mean direction). Together these features provided a comprehensive description of prevailing sea-surface conditions. Significant wave height, mean and peak periods, and mean wave direction captured the bulk of wave climate variability, while sea surface temperature and sea level anomaly represented the thermal and dynamic state of the ocean. Near-surface wind speed acted as the primary driver of wave generation. This set of variables was chosen to balance explanatory power with model interpretability.

Static ecological and geomorphic layers were then brought into the same spatial frame. Mangrove condition was represented using rasters of above-ground biomass, 95th percentile canopy height, and 95th percentile maximum tree height. Each raster was reprojected to WGS84 (EPSG:4326, the standard global geographic coordinate system using latitude and longitude) and resampled onto the original CMEMS grid, with nearest-neighbor resampling for categorical or sparse ecological layers to avoid smoothing, and bilinear resampling for bathymetry to retain continuous gradients. Pixels without mangrove data were set to zero so that absence is encoded explicitly rather than as missing. Bathymetry was added as seabed depth and interpolated to the grid resolution using bilinear resampling.

Coral features were represented in three complementary forms on the CMEMS grid. First, reef polygons were cleaned to resolve minor topology issues and then rasterized into a binary presence mask, ensuring conservative coverage at grid edges. Second, we generated a continuous surface of distance to the nearest reef, expressed in kilometers, by applying an Euclidean distance transform that accounted for the different scaling of latitude and longitude. In practice, this meant treating north–south distances as approximately 111 kilometers per degree of latitude, and east–west distances as progressively shorter depending on latitude due to the convergence of meridians. Third, to quantify the amount of reef within each grid cell, we intersected reef polygons with the cell footprints after transforming both into an equal-area projection, and then calculated reef area in square kilometers. This combination of metrics allowed us to distinguish between the effects of reef proximity and the actual areal extent of reef habitat.

All dynamic and static inputs were then merged into a single multi-variable xarray dataset aligned on the CMEMS grid. Static layers were broadcast across time to match the wave time index. We constructed an inclusion mask that kept ocean cells wherever the reference wave field was valid, while also retaining land cells that contained mangroves so that coastal vegetated pixels were not dropped at the land–sea interface. Spatial dimensions were stacked into a single index to facilitate downstream learning tasks. Three-hourly CMEMS records were aggregated to daily means to reduce high-frequency variance and improve signal-to-noise for model training. The

TABLE I

Overview of data categories, features, and their roles in the Jamaica coastal resilience analysis.

Category	Features	Description	Year	Citation
Wave	Significant wave height Maximum wave height Mean wave direction Primary swell height Wind–sea height Wind–sea period Wind–sea direction Spectral peak period	Key sea-surface wave metrics and partitions on a 0.083° grid.	2023-2024	[14]
Mangrove	Above-ground biomass 95th-percentile canopy height 95th-percentile maximum tree height	Biomass density and canopy structure indicators for mangrove stands.	2016	[15]
Coral	Reef presence mask Distance to nearest reef Reef area per cell	Binary coverage, proximity, and true area of coral reefs in each grid cell.	2020	[16]
Bathymetry	Seabed elevation (depth)	Underwater depth grid for wave shoaling and breaking analysis.	2020	[16]

dataset was then converted to a tidy DataFrame in which each row represented a unique day–cell pair and columns corresponded to dynamic wave properties, static mangrove metrics, coral mask, coral distance, coral area, and bathymetry. This processing pipeline yielded a consistent, interpretable feature table that preserved key coastal processes while maintaining fidelity to the original measurement scales.

C. Model Tuning

The prepared feature table was first normalized using a min–max scaler so that all predictors were placed on a common scale. The dataset was then divided into training and testing sets to allow the model to be evaluated on unseen observations. Specifically, an 80:20 split was applied, ensuring that the model was evaluated on a distinct portion of unseen data. The target variable was chosen to be significant wave height, which represents the average height of the highest one-third of waves in a given period. This parameter is widely used in oceanography as it provides a robust measure of sea state and is a key indicator of coastal vulnerability, since larger wave heights are strongly associated with flooding, erosion, and damage to coastal ecosystems and infrastructure.

An XGBoost regression model was then trained on the processed features to capture the relationship between wave height and the ecological and geomorphic predictors. Hyperparameter tuning was carried out using grid search in order to determine the optimal model configuration. Model performance was evaluated on the held-out test set, with the coefficient of determination (R^2) used as the evaluation metric.

D. Feature Importance

Feature importance was derived directly from the trained XGBoost regression model. XGBoost evaluates importance by tracking how often and how effectively each predictor is used to split the data across the ensemble of regression trees. In practice, this involves measuring the average gain in predictive accuracy or reduction in error whenever a feature is used for a split. The result is a relative importance score for each variable, which can then be ranked to highlight the predictors that contributed most to explaining variation in significant wave height.

E. SHAP Values

After the XGBoost regression model was trained, SHAP (SHapley Additive exPlanations) was applied to interpret the outputs. A tree-based SHAP explainer was initialized using the fitted model, and SHAP values were computed for the full feature matrix. These values quantify the marginal contribution of each predictor to individual predictions, with positive values indicating upward influence relative to the mean and negative values indicating downward influence. Aggregating absolute SHAP values across all samples provides a measure of global importance, allowing identification of the ecological and geomorphic drivers most consistently influencing predicted wave heights. This approach provides a transparent and theoretically consistent framework for interpreting complex ensemble models. [9].

IV. Results

The XGBoost regression model achieved a test R^2 of 0.919, indicating strong predictive skill even after excluding collinear predictors such as maximum wave height. As seen in Table II, the most influential drivers were the mean period of the wind-sea (0.365) and the mean period of the primary swell (0.150), followed by the overall spectral peak period (0.106). Among the static coastal features, reef area (0.067) and bathymetry

TABLE II
XGBOOST FEATURE IMPORTANCE SCORES.

Feature	Importance
Wind-sea mean period (Tm01)	0.365
Swell mean period (Tm01)	0.150
Spectral peak period (Tp)	0.106
Reef area (km^2)	0.067
Bathymetry (m)	0.054
Mangrove max canopy height (P95)	0.051
Distance to reef (km)	0.047
Mangrove above-ground biomass	0.046
Wind-sea mean direction (°)	0.043
Mangrove canopy height (P95)	0.039
Mean wave direction (°)	0.032

TABLE III
GROUPED XGBOOST FEATURE IMPORTANCES

Group	Sum importance	Share (%)
Waves	0.696	69.6
Reefs	0.114	11.4
Mangroves	0.136	13.6
Bathymetry	0.054	5.4

(0.054) were the most important, with mangrove maximum canopy height (0.051), distance to reefs (0.047), above-ground biomass (0.046), and mangrove canopy height at the 95th percentile (0.039) also contributing. Directional parameters such as wind-sea direction (0.043) and mean wave direction (0.032) ranked lower but still provided additional explanatory value. These results show that while offshore wave spectral properties dominate predictions, ecological and geomorphic features also shape nearshore conditions.

The grouped importance scores in Table III show that wave spectral properties dominate model predictions, accounting for more than three quarters of the explained importance. However, nature-based features collectively represent a substantial share: reefs contribute about 12% and mangroves nearly 15%, with bathymetry adding another 6%. This highlights that while offshore wave dynamics are the primary drivers of significant wave height, ecological and geomorphic features provide a measurable secondary influence. Notably, mangroves emerge with comparable importance to reefs, highlighting their potential role in wave attenuation in this region.

The SHAP value analysis in Table IV similarly identified the mean period of the wind-sea as the dominant predictor, with a mean absolute contribution nearly an order of magnitude greater than any other feature. Secondary contributions came from wind-sea direction and distance to reefs, with smaller but consistent effects from the spectral peak period and mean

TABLE IV
GLOBAL SHAP FEATURE IMPORTANCE

Feature	Mean |SHAP|	Spearman ρ
Wind-sea mean period (Tm01)	0.919	0.91
Wind-sea mean direction (°)	0.106	-0.06
Distance to reef (km)	0.098	0.33
Spectral peak period (Tp)	0.093	0.10
Mean wave direction (°)	0.082	0.05
Reef area (km^2)	0.077	-0.27
Bathymetry (m)	0.059	-0.21
Mangrove max canopy height (P95)	0.056	-0.07
Mangrove above-ground biomass	0.050	-0.04
Mangrove canopy height (P95)	0.047	-0.02
Swell mean period (Tm01)	0.044	0.11

TABLE V
GROUPED SHAP IMPORTANCE BY FEATURE CATEGORY

Group	Features in group	Sum mean |SHAP|
Waves	6	1.244
Reefs	3	0.175
Bathymetry	1	0.059
Mangroves	3	0.154

wave direction. Grouped importance scores showed that wave properties explained the majority of predictive power $\approx$1.24 in summed mean absolute SHAP values), but reefs ($\approx$0.18) and bathymetry ($\approx$0.06) still accounted for meaningful fractions. Notably, mangrove features together contributed $\approx$0.15, comparable in scale to bathymetry, indicating that while their individual influence is modest, their collective role provides a measurable effect on nearshore wave conditions. Reefs contributed both through proximity and area, with SHAP directionality indicating that larger reef areas and closer reef proximity reduced predicted wave heights. Bathymetry also acted in the expected way, with shallower depths associated with lower wave heights. Mangrove features explained a smaller proportion of the variance in this configuration, though they were retained in the model and contributed in specific cases.

To visualize the SHAP global values, Figure 1 shows a beeswarm plot illustrating the relative importance of each predictor and whether higher or lower feature values increase or decrease predicted wave heights.

V. DISCUSSION

Both the XGBoost feature importance rankings and the SHAP value analysis consistently highlight the primacy of wave period metrics, particularly the mean period of the wind-sea, in driving predicted significant wave height. At the same time, the two approaches agree that coastal ecosystems and geomorphic settings are not negligible. Reefs and bathymetry emerge as consistent contributors, while mangrove features,

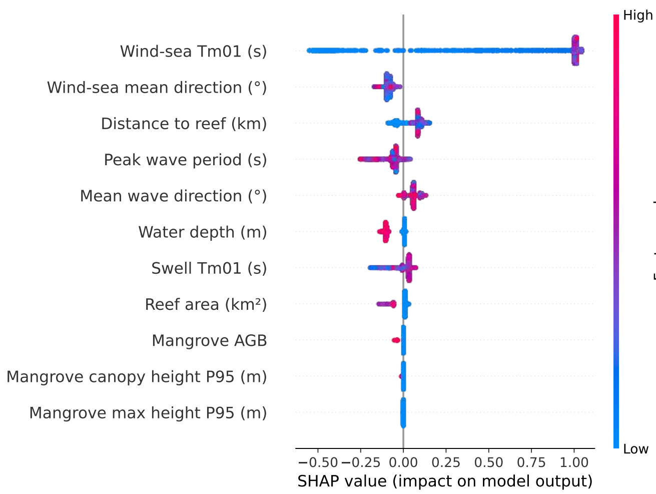

Fig. 1. Visualization of SHAP Summary: Global Feature Influence

though less influential at the aggregated scale, still appear in the importance rankings. SHAP further clarifies the protective influence of reefs and shallow bathymetry, demonstrating that these nature-based solutions actively reduce wave height, even if their explanatory power is smaller relative to offshore wave dynamics. Taken together, the results show that while offshore spectral properties dominate, ecosystems such as reefs and mangroves continue to provide measurable and protective effects that support their role in coastal resilience.

A key challenge in this study was the lack of consistency across data sources, particularly in spatial resolution and temporal coverage. For example, wave metrics such as significant wave height and mean wave direction were obtained from the Copernicus Marine Service reanalysis for 2023–2024, while mangrove biomass and canopy height indicators dated back to 2016. Coral reef datasets describing coverage and proximity, along with the bathymetry grid used for wave analysis, were released in 2020. Aligning these heterogeneous datasets required interpolation and regridding, which introduced additional uncertainty and complicated model performance. The issue was both technical and conceptual , since the model combined wave observations from the present with ecological and geomorphic information that reflected conditions several years earlier. Additionally, differences in granularity of data meant that smaller reefs and forested patches, which can play an important role in buffering localized wave energy, may be underrepresented. This can lead to the potential loss of critical protective features in certain areas of the region. This highlights that one of the biggest challenges in developing machine learning models for coastal resilience involving dealing with fragmented and uneven data sources.

One limitation of existing coastal hazard indices is that their formulation often relies on simple additive or multiplicative combinations of normalized variables, which are not necessarily data-driven and may lack robustness in how different factors are weighted. In contrast, our methodology introduces a data-driven framework that leverages feature importances derived from machine learning models to objectively guide the weighting process in constructing a coastal vulnerability index.

The following are works involving the assessment of Coastal vulnerability in Jamaica: the Comparative Coastal Risk Index (CCRI) [10], the ecosystem-based Coastal Vulnerability Index (CVI) [17], and the Climate and Ocean Risk Vulnerability Index (CORVI) [18]. Each relies on composite formulations that integrate physical forcing, socioeconomic conditions, and the protective influence of ecosystems such as mangroves and coral reefs.

The CCRI is expressed as the geometric mean of hazard, exposure, and vulnerability scores:

$$\mathrm{CCRI} = \sqrt[3]{HS \times ES \times VS} \tag{1}$$

The hazard score (HS) combines normalized values of wave height, storm surge, wind, and sea-level anomalies (El Niño). Exposure (ES) sums the proportion of population, GDP, cropland, urban areas, and ecosystems in flood zones, while vulnerability (VS) includes infant mortality, malnutrition, and income inequality [10]. Ecosystems such as mangroves reduce ES by lowering the share of assets at risk, whereas degraded systems increase it. For Jamaica, CCRI values indicate an "elevated risk" category.

The CVI uses a geometric mean of ranked parameters:

$$\mathrm{CVI} = \sqrt{\frac{a \times b \times c \times d \times e \times f}{n}} \tag{2}$$

where a-f are ranked (1-5) values for slope, geomorphology, sea-level rise, shoreline change, wave height, and tidal range. This extension introduces a ecosystem protection factor g:

$$\mathrm{CVI}_{eco} = \sqrt{\frac{a \times b \times c \times d \times e \times f}{g \times n}} \tag{3}$$

In practice, g is not calculated from a continuous function but rather assigned as an ordinal rank (1-5) based on the presence, extent, and condition of protective ecosystems. Applied to Whitehouse, Jamaica, this approach classified the coast as highly vulnerable despite some ecosystem presence, reflecting the degraded state of protective habitats [17].

CORVI evaluates risk at the city scale using approximately 90 indicators, grouped into ten categories across ecological, economic, and social/political domains. Each indicator is normalized to a 1-10 scale, and category scores are averaged:

$$\mathrm{CORVI}_{category} = \frac{1}{n}\sum_{i=1}^{n} I_i, \quad I_i \in [1, 10] \tag{4}$$

Ecological indicators include mangroves, coral reefs, seagrass beds, fisheries pressure, and water quality. These are equally weighted within the ecological domain, and no explicit prioritization is given to mangroves or reefs relative to other indicators. In Kingston, high scores for mangroves (7.91), coral reefs (7.86), and seagrass beds (8.13) reflected ecosystem degradation, contributing to the city's high coastal risk. [18].

A common limitation across CCRI, CVI, and CORVI is that ecological and hazard variables are combined through simple ranking, summation, or equal-weighted averaging schemes. These approaches are not inherently data-driven, and the weighting of ecological factors is often based on expert judgment or qualitative scoring rather than quantitative evidence. Employing a data-driven methodology, such as using feature importances from machine learning models, can provide objective, evidence-based weightings that strengthen the robustness of coastal vulnerability indices and improve their applicability for decision-making. In this way, indices that currently depend on static or subjective scoring can be enhanced with dynamic, data-driven weights , yielding more reliable assessments of the protective role of ecosystems and supporting more effective climate resilience planning.

VI. Conclusion and Future work

This work demonstrates a framework through which data-driven weights can be integrated into coastal vulnerability indices, enabling more objective and locally responsive assessments for small island developing states. By integrating XGBoost-derived feature importances with SHAP-based interpretability, the approach provides an objective weighting of geological and ecological factors, enhancing the representation of nature-based solutions and reducing the limitations of fixed expert-driven schemes. This contributes to more reliable and actionable assessments that can better inform adaptation planning and policy.

Future work will extend this framework by developing more detailed models, integrating a wider variety of datasets, and improving data quality, including the use of longer time series to capture historical variability and long-term trends. Building on this foundation, the framework will be expanded to other Caribbean SIDS for validation and scaling, and ultimately to additional regions to strengthen evidence based coastal resilience strategies.

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