PEER-REVIEWED ARTICLE

Risk assessment and mitigation measures of maritime navigation in the Caribbean Sea

Authors

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Abstract

The Caribbean Sea, a vital maritime corridor with high vessel traffic and strategic access to the Panama Canal, faces growing navigational risks. This study develops a probabilistic risk assessment model incorporating vessel and environmental conditions, enhanced by an Artificial Neural Network to estimate incident probability. By leveraging Automatic Identification System (AIS) data and machine learning, mitigation scenarios were evaluated, confirming their effectiveness in reducing risk. The methodology advances traditional models by integrating multiple cause-related factors, offering a more comprehensive understanding of maritime safety. This research highlights the value of AIS and AI-driven approaches in enhancing risk mitigation and navigational resilience in the Caribbean Sea.

Keywords

Caribbean Sea · AIS · probabilistic risk assessment · vessel traffic · artificial neural network · machine learning · maritime accidents

Resumé

La mer des Caraïbes, corridor maritime vital caractérisé par un trafic maritime intense et un accès stratégique au canal de Panama, est confrontée à des risques de navigation croissants. Cette étude développe un modèle probabiliste d'évaluation des risques intégrant les conditions environnementales et celles des navires, amélioré par un réseau neuronal artificiel permettant d'estimer la probabilité d'incidents. En exploitant les données du système d'identification automatique (AIS) et l'apprentissage automatique, des scénarios d'atténuation ont été évalués, confirmant leur efficacité dans la réduction des risques. La méthodologie améliore les modèles traditionnels en intégrant plusieurs facteurs liés aux causes, offrant ainsi une compréhension plus complète de la sécurité maritime. Cette recherche souligne la valeur des approches basées sur l'AIS et l'IA pour améliorer l'atténuation des risques et la résilience de la navigation dans la mer des Caraïbes.

Resumen

El Mar Caribe, un corredor marítimo vital con un alto tráfico de buques y un acceso estratégico al Canal de Panamá, afronta crecientes riesgos a la navegación. Este estudio desarrolla un modelo probabilístico de evaluación de riesgos que incorpora las condiciones de los buques y del medio ambiente, mejorado por una Red Neuronal Artificial para estimar la probabilidad de incidentes. Aprovechando los datos del Sistema de Identificación Automática (AIS) y el aprendizaje automático, se evaluaron escenarios de mitigación, confirmando su eficacia para reducir el riesgo. La metodología mejora los modelos tradicionales al integrar múltiples factores relacionados con las causas, ofreciendo una comprensión más completa de la seguridad marítima. Esta investigación resalta el valor de los enfoques basados en AIS e IA para mejorar la mitigación de riesgos y la resiliencia de la navegación en el Mar Caribe.

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1 Introduction

Global maritime trade is facilitated by an intricate web of shipping routes shaped by geographic constraints, chokepoints, and strategic trade corridors (UNCTAD, 2019). Maritime transportation accounts for over 90 % of international commerce and is a critical driver of economic development, particularly in developing regions such as the Caribbean (IMO, 1972). Strategically positioned along East–West and North–South trade flows and adjacent to the Panama Canal, the Caribbean Sea functions as a major hub for global transhipment activities. Growing vessel traffic, offshore operations, and energy exploration further heighten its economic importance (Rodrigue, 2019; Sabonge, 2014). Transhipment activity has expanded into a triangular configuration linking the key ports of Freeport, Colon, and Port of Spain (Fig. 1), which anchor the region's integration into the global maritime network and support hinterland development (Wilmsmeier & Sánchez, 2009). Despite the geographic dispersion of the Caribbean Community and Common Market (CARICOM) member states, maritime navigation unites the region economically, facilitating trade in energy, agriculture, manufactured products, and consumer goods (Wilmsmeier & Sánchez, 2009).

Nevertheless, increasing maritime activity heightens navigational risks, particularly in confined waterways and heavily trafficked shipping lanes (Styliadis & Koliousis, 2012). Despite significant advances in navigation and communication technologies, the maritime industry remains vulnerable. Operational complexity, unpredictable environmental conditions, and the continued lack of surveys for over 80 % of the Caribbean Sea leave the region exposed to collisions, groundings, and environmental disasters (MarineMarico, 2013). Despite advancements, maritime accidents continue to occur, underscoring the importance of understanding incident causation and developing proactive risk mitigation strategies (Kristiansen, 2005). Given the region's reliance on maritime transport and its growing role in international trade, there is an urgent need to assess and manage the risks associated with increased vessel traffic. This includes examining the parameters that influence maritime accidents and understanding the consequences of accidents on the marine environment, human safety, and economic stability (Calder & Kurt, 2009). The designation of the Caribbean Sea as an International Convention for the Prevention of Pollution from Ships (MARPOL) Special Area underscores the urgency of improving maritime safety standards (IMO, 2012). Modern navigation technologies, particularly the Automatic Identification System (AIS), have revolutionized maritime monitoring by enabling real-time tracking and analysis of vessel behaviour (Eriksen et al., 2006). However, existing risk models for the Caribbean often remain limited to restricted waters or omit key environmental and vessel-specific factors. To address this gap, this study leverages one year of Satellite Automatic Identification System (S-AIS) data and applies an Artificial Neural Network (ANN) to develop a probabilistic risk assessment model integrating vessel, environmental, and charting conditions for the Caribbean Sea. The model quantifies incident probability, evaluates targeted mitigation strategies, and supports data-driven decision-making to enhance navigational safety and resilience across the region's complex maritime domain.

2 S-AIS data and vessel traffic analysis in the Caribbean Sea

S-AIS data offers continuous global tracking of vessel location, course, and speed, revolutionizing maritime surveillance (Eriksen et al., 2006). In this study, S-AIS data purchased from ORBCOMM was used to determine vessel traffic density in the Caribbean Sea by extracting vessel positions, mapping high-traffic zones, and generating track lines for analysis. However, several limitations were encountered. Errors in Maritime Mobile Service Identity (MMSI) values were common, including duplicate identifiers and inconsistent formatting. Type 5 AIS messages, containing static and voyage-related vessel data, were often missing or miscatalogued. Additionally, AIS units were sometimes reset or switched off, leading to positional gaps particularly among smaller, locally operating vessels, as also documented by Maharaj (2020). Signal interruptions from reliance on low Earth orbit satellites caused fragmented tracks (Jelavić et al., 2008), while both satellite and terrestrial AIS suffered from asynchronous transmissions and limited bandwidth, leading to message collisions and data loss (Pedersen, 2002; Carson-Jackson, 2012). To address these issues, a custom MATLAB script retrieved missing Type 5 data from *MarineTraffic* and *VesselFinder* using MMSI queries to obtain International Maritime Organization (IMO) number, tonnage, dimensions, and flag. This information was then linked to the reconstructed vessel tracks, and misplaced routes caused by coverage gaps were corrected with verified *MarineTraffic* navigational data. In total, 67,289 vessel tracks were reconstructed for 2016, providing a detailed picture of vessel movements and maritime corridors sufficient for developing the regional risk assessment model (Fig. 2).

2.1 Port to port activity in the Caribbean Sea

To better understand the flow and concentration of vessel movements within the Caribbean Sea, a detailed port-to-port analysis was performed using the refined S-AIS data. This analysis leveraged spatially referenced vessel track lines entering and exiting designated port areas, represented by geofenced rectangular zones, to identify the start and end of voyages. These geofences included both regional ports and boundary points at the edges of the Caribbean Sea, which allowed for the classification of local, regional, and international traffic patterns.

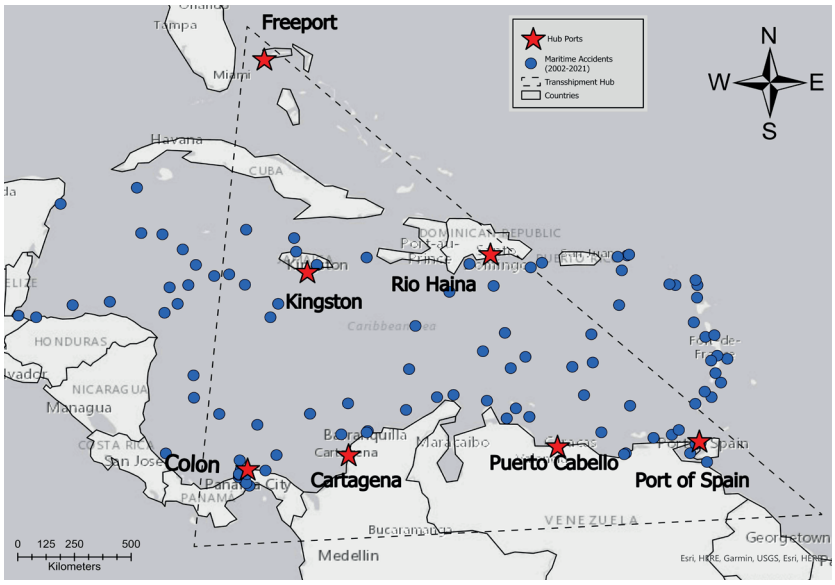


Fig. 1 Caribbean transshipment triangle with hub ports and maritime events (2002–2021).

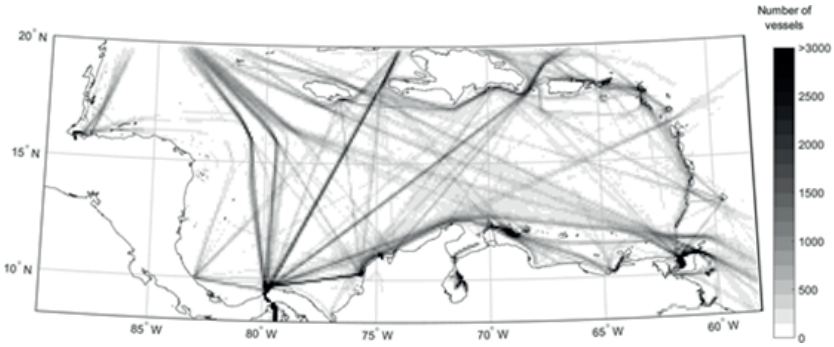


Fig. 2 Number of vessels passing through 0.1° cells in 2016.

2.1.1 Cargo port calls

The cargo port call analysis revealed over 2,000 cargo transits in the Caribbean Sea for the year 2016, with dense inter-island and international cargo routes represented in varying intensities (Fig. 3). For this study, "cargo" includes container ships, general cargo vessels, bulk carriers, roll-on/roll-off (Ro-Ro) vessels, refrigerated cargo ships, heavy load carriers, livestock carriers, and other specialized dry cargo ships as classified in the S-AIS dataset. Lighter passages indicated regular regional trading, while heavier transit lines particularly between the Panama Canal and the Mexico-Cuba and Cuba-Haiti borders reflected high-frequency movements associated with major global trade lanes. Ports such as Mariel in Cuba, Cristobal in Panama, and Cartagena in Colombia emerged as key cargo hubs due to their proximity to the Panama Canal and investments in deep-water and transhipment infrastructure. Table 1 highlights the busiest cargo ports, with the Cuba-Haiti and Mexico-Cuba border regions registering over 10,000 port calls each. These ports benefit from their strategic positioning near global trade lanes and strong bilateral trade relationships. High volumes were also noted between the Lesser Antilles and the eastern maritime boundary, indicating significant regional connectivity.

2.1.2 Passenger port calls

For this analysis, passenger vessels included both dedicated passenger ships (e.g., cruise ships, ferries) and mixed-use passenger vessels, reflecting the operational realities of Caribbean maritime transport. Passenger traffic, vital to the tourism-dependent economies of the Caribbean, was found to be densely concentrated in areas such as Puerto Rico, the U.S. and British Virgin Islands, and the Lesser Antilles (Fig. 4). Notably, the Port of Fajardo in Puerto Rico recorded the highest number of passenger journeys 7,416 in total due to frequent sea bridges to nearby islands such as Vieques and Culebra. Passenger routes also showed intense clustering around Charlotte Amalie, Guadeloupe, and Turks and Caicos (Table 2). These ports facilitate inter-island cruise operations and ferry services, reflecting the regional importance of tourism-related maritime transport. The concentration of these movements reinforces the critical role of port infrastructure in supporting tourism, employment, and local development.

2.1.3 Tanker port calls

Tankers were classified to include vessels transporting liquid bulk cargo such as oil, chemicals, liquefied gas, asphalt, and other specialized liquid products. Categories included Asphalt Tanker, Chemical Tanker, Crude Oil Tanker, LPG/LNG Tanker, Products Tanker, Oil/Chemical Tanker, and other related liquid-cargo vessel types. The Caribbean's role in the global oil and gas trade was evident with over 19,000 tanker transits recorded in 2016 (Fig. 5). Traffic was dominated by routes connecting Venezuela, Panama, Mexico, and Trinidad and Tobago. The Mexico-Cuba Northwest to East Border route recorded over 7,000 tanker journeys, underscoring the region's use as a passage for crude oil and gas to North America. Ports such as Punta Cardon and Caicara in Venezuela, as well as Curacao's Port of Willemstad, were identified as key tanker hubs (Table 3). Trinidad's Point Fortin also demonstrated significant regional tanker traffic. These ports serve as vital nodes for both export and transhipment of oil and gas products. Notably, intra-Venezuelan movements between Maracaibo, Punta Cardon, and Caicara illustrated high national-level oil distribution.

The port-to-port analysis provides critical insight into the volume, type, and pattern of vessel activity within the Caribbean Sea. It confirms the region's status as a central corridor for global and regional maritime flows, connecting numerous systems of circulation. The concentration of cargo, passenger, and tanker operations within confined geographic spaces underscores the need for robust safety protocols, modernized port infrastructure, and environmental protection strategies. With increasing vessel sizes, rising trade volumes, and growing cruise tourism, the

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risks of collision, congestion, and pollution are heightened. Regional ports vary in capacity and efficiency, which can affect their ability to safely accommodate rising traffic. Given the Caribbean's economic dependence on maritime transport and its designation as a MARPOL Special Area, targeted efforts are essential to enhance navigational safety, enforce international regulations, and invest in risk mitigation and monitoring systems. This data-driven overview not only maps critical maritime gateways but also serves as a foundation for assessing vulnerabilities and prioritizing future infrastructure and policy interventions across the region.

3 Risk assessment strategies in maritime navigation

Accurately assessing the risk of maritime navigation has become increasingly complex due to the dynamic nature of the marine environment and the intensity of vessel traffic. Traditionally, maritime risk assessment models have relied on statistical and geometric methodologies to evaluate navigational hazards, particularly within confined waterways such as ports and straits (Macduff, 1974; Fujii, 1974; Kristiansen, 2005). These models often provide a static or simplified view of vessel movement, focusing largely on linear traffic flows and spatial proximity calculations. While foundational to the discipline, such approaches fall short of capturing the multifactorial risks present in open seas and broader maritime domains (Mazaheri et al., 2014). With the advent of AIS data and enhanced computational capabilities, maritime risk assessment has shifted toward more dynamic, data-driven methodologies (IALA, 2019; Goerlandt & Montewka, 2015). AIS enables the capture of real-time vessel movements, producing rich datasets that reflect the spatial–temporal complexities of modern maritime traffic. This has paved the way for simulations and probabilistic models capable of representing vessel interactions and predicting collision scenarios under varied conditions (Chen et al., 2019; Montewka et al., 2011).

Among early foundational models, Blackwell's ship domain theory served as a cornerstone for collision risk evaluation, focusing on the spatial interaction zones of navigating vessels (Blackwell, 1989). However, many traditional models, while incorporating AIS data, remain limited in scope, primarily addressing risk within restricted waters and neglecting broader risk-inducing variables such as vessel age, flag state, navigational equipment, sea conditions, bathymetry, Aids to Navigation (AtoN), and regional hazards (Kristiansen, 2009; Montewka et al., 2010). Approaches by Macduff (1974), Fujii (1974), Pedersen (2002), Kaneko (2002), and COWI (2008) typically employ geometric probabilities, historical data, and simplified assumptions about vessel behaviour. These have provided valuable insights in confined waterways but perform poorly in open-sea contexts, where they often assume uniform traffic density, overlook external factors such as weather

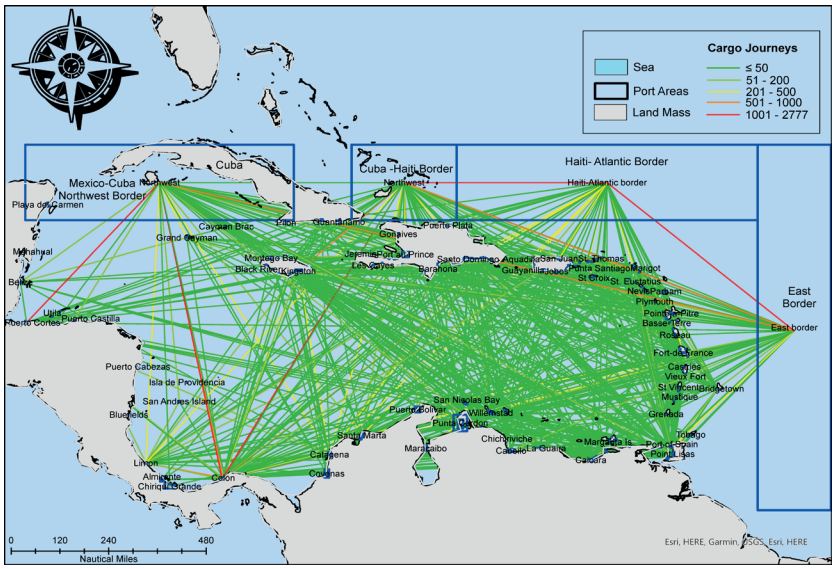


Fig. 3 Cargo Vessel Port Call and Track Density Patterns in the Caribbean Sea, 2016.

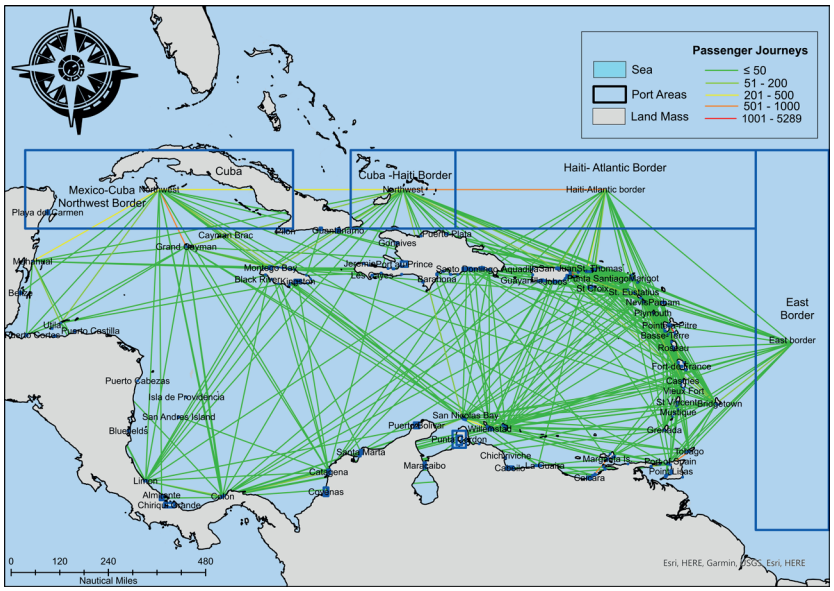


Fig. 4 Passenger Vessel Port Call and Track Density Patterns in the Caribbean Sea, 2016.

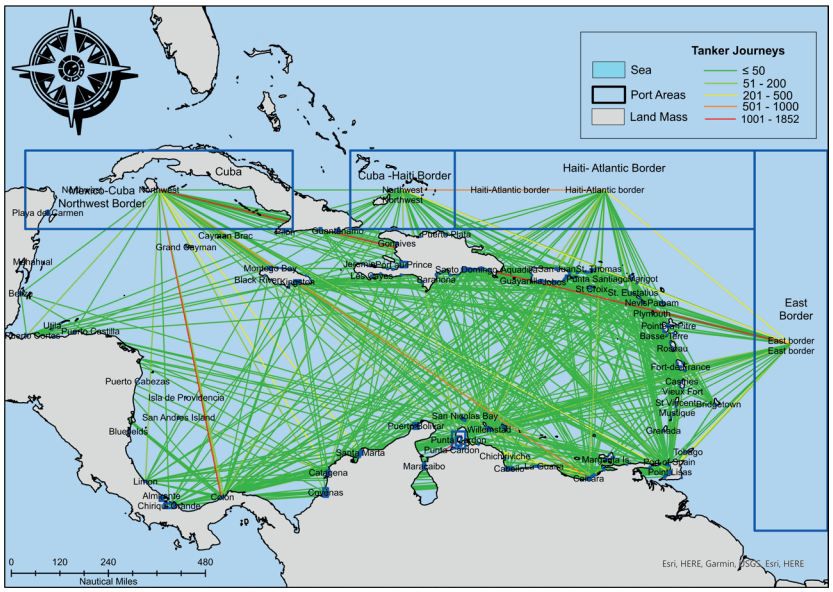


Fig. 5 Tanker Vessel Port Call and Track Density Patterns in the Caribbean Sea, 2016.

Table 1 Cargo journeys within the Caribbean Sea, 2016.

Country	Port	Number of journeys
Cuba-Haiti border	Northwest	10682
Mexico-Cuba border	Northwest	10502
Panama	Canal	7614
Panama	Cristobal	6962
Haiti-Atlantic border	Haiti-Atlantic border	6738
East border	East border	5990
Columbia	Cartagena	5013
Jamaica	Port of Kingston/Port Royal	4181
Dominican Republic	Santo Domingo	2858
United States of America	San Juan	2783

Table 2 Passenger journeys within the Caribbean Sea, 2016.

Country	Port	Number of journeys
United States of America	Port of Fajardo	7416
American Virgin Islands	Port of Cruz Bay	5474
American Virgin Islands	Redhook Bay	5345
United States of America	Ensenada Honda Harbour	3769
United States of America	Port of Vieques	3750
American Virgin Islands	Charlotte Amalie	2399
British Virgin Islands	Road Harbour	1891
Guadeloupe	Port of Pointe-a-Pitre	1709
Guadeloupe	Port of Grand-Bourg	1494
Haiti-Atlantic Border	Haiti-Atlantic Border	1469

Table 3 Tanker journeys within the Caribbean Sea, 2016.

Country	Port	Number of journeys
Mexico-Cuba Border	Northwest	7124
East Border	East Border	3615
Venezuela	Port of Punta Cardon	2913
Panama	Canal	2628
Haiti-Atlantic Border	Haiti-Atlantic Border	2247
Cuba-Haiti Border	Northwest	2238
Venezuela	Port of Caicara	1689
Netherlands Antilles	Port of Willemstad	1495
Venezuela	Los Boqueticos	992
Columbia	Cartagena	940

and human error, and fail to account for dynamic vessel interactions (Goerlandt & Montewka, 2015; Chen et al. 2019).

Contemporary AIS-based models have improved understanding of vessel movement patterns and collision probabilities. Case studies employing Monte Carlo simulations (Miller et al., n.d.), Cellular Automata (Qu & Meng, 2012), and Convolutional Neural Networks (Georlandt et al., 2020) demonstrate considerable potential, yet still frequently omit critical variables such as vessel flag, age, and weather. They also often rely on static causation probabilities, suffer from incomplete databases, and rarely undergo real-world validation (Ylitalo, 2010; Mazaheri et al., 2014). Many are geographically specific, such as the Land Information New Zealand (LINZ) strategy for the South Pacific and cannot

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be applied elsewhere without modification (Riding & Rawson, 2015). International Association of Marine Aids to Navigation and Lighthouse Authorities (IALA) based models like IALA Waterway Risk Assessment Program (IWRAP) also assume narrow, fixed traffic corridors and do not scale well to open seas where vessel paths are highly variable and multidirectional.

Recent comprehensive reviews on maritime risk analysis methods have further broadened the field. Li et al. (2012) provide an overview of quantitative risk assessment models; Kulkarni et al. (2020) assess prevention-oriented waterway risk management strategies and outlines methods for detecting near-miss events using AIS. Collectively, these works span traditional quantitative models through to AI-based and non-accident event detection techniques, setting the stage for recent research integrating artificial intelligence and spatial analytical approaches. For example, Chen et al. (2019) reviewed probabilistic risk-analysis methods for ship–ship collisions, highlighting persistent difficulties in modelling causation due to limited human and organizational factor data. Yang et al. (2023) developed a hybrid Bayesian network and systems-theoretic process analysis (STAMP/STPA) model, exemplifying multi-method integration in maritime risk modelling. Rawson and Brito (2022) expanded the AI perspective with a review of supervised machine learning for maritime accident prediction, severity estimation, ship detentions, and collision risk modelling, identifying challenges in data representativeness, model transparency, and validation issues highly relevant to open-sea contexts. Complementing these approaches, Feng et al. (2025) demonstrated the value of global spatial accident hotspot mapping using kernel density estimation and K-means clustering, revealing marked spatial heterogeneity in risk across chokepoints, traffic hubs, vessel types, and time periods.

Despite these advances, few studies have applied such integrated approaches to the Caribbean Sea or incorporated the full range of vessel-specific, environmental, and charting parameters needed for regional-scale, open-sea risk analysis. To address this gap, this research develops a holistic risk model that moves beyond traditional traffic simulations. ANNs are particularly well-suited to this task, as they can recognise nonlinear patterns and adapt to evolving maritime conditions while processing large datasets with multiple input variables (Supomo & Nugroho, 2021). This study therefore employs an ANN-based approach that combines AIS data with vessel characteristics, environmental data, and navigational parameters to estimate maritime incident probabilities. The model supports robust, data-driven decision-making for targeted risk mitigation in the Caribbean Sea and other complex maritime domains.

4 Method

To construct an accurate and robust maritime risk assessment model, a comprehensive review of global maritime events was conducted using data from the Global Integrated Shipping Information System (GISIS), maintained by the IMO. This dataset contained 6,260 marine casualties and incidents reported globally between January 2002 and December 2021. Combined with prior literature, this 20-year analysis was instrumental in identifying recurring causal patterns and confirming the most significant and recurrent risk factors in the Caribbean context (Maharaj et al., 2025). The selected variables were chosen to reflect both navigational hazards and the region's unique data availability. Several key causal factors were identified: velocity of ocean currents, availability and reliability of AtoN, Category Zone of Confidence (CATZOC) from hydrographic surveys, known navigational hazards, bathymetric characteristics, vessel nationality (flag), and vessel age. Vessel movement data from S-AIS for 2016 was used to analyse traffic density within the Caribbean Sea, representing a stable period in regional traffic patterns. Vessel density is a fundamental indicator of collision risk and was treated as a core modelling variable. Supporting spatial datasets, including bathymetry and CATZOC classifications, were sourced from the United Kingdom Hydrographic Office (UKHO, 2019) in GIS-compatible formats. Each variable was processed into a 1 km² grid within the Caribbean Maritime Exclusive Economic Zone (EEZ) and prepared for integration into the ANN model. Detailed derivations included:

- Vessel traffic density: Number of vessel transits per 1 km² from 2016 S-AIS data (ORBCOMM).
- Bathymetry: Average sounding depth per grid cell (UKHO, 2019).
- Proximity to navigational hazards: Density of reefs, wrecks, shoals, pipelines, and other hazards (UKHO, 2019).
- Proximity to AtoN: Density of AtoN per grid cell (UKHO, 2019).
- Current velocity: Long-term hydrodynamic averages interpolated using kriging (UKHO).
- CATZOC quality: Hydrographic survey accuracy and seafloor coverage (UKHO, 2019).
- Chart age: Years since last survey based on UKHO metadata.
- Vessel age: Percentage distribution of vessel ages aggregated from GISIS data, calculated only for grid cells with reported accidents.
- Flag state: Percentage distribution of vessel flags aggregated from GISIS data, calculated only for grid cells with reported accidents.

4.1 Comparison with earlier work

This selection of navigational risk factors builds on, yet diverges from, earlier maritime risk assessment methods. Classic models, such as those by Macduff (1974), Fujii (1974), Pedersen (2002), and the IALA Waterway Risk Assessment Program (IWRAP), have primarily emphasised traffic geometry, vessel encounter rates, and collision probabilities in restricted

waters. While effective in ports and channels, these models are less suited to the open-sea conditions of the Caribbean, where vessel movements are multidirectional, traffic density is uneven, and environmental conditions are highly variable. Some variables in this study such as traffic density and flag state are common to previous approaches (Montewka et al., 2011; Goerlandt & Montewka, 2015). Others, such as CATZOC, chart age, AtoN density, and current velocity, are rarely integrated into probabilistic models but are particularly relevant in this study. CATZOC and chart age address hydrographic uncertainty, which is critical in a region where over 80 % of waters remain un-surveyed to modern standards (MarineMarico, 2013). Similarly, current velocity, although noted in navigation literature (Kristiansen, 2005), has seldom been operationalised in ANN-based maritime risk modelling.

4.2 Approach to risk assessment

The primary objective of this study was to develop a comprehensive risk assessment model to estimate the probability of maritime events based on contributory factors. This was achieved by integrating domain knowledge, historical accident data, and spatial risk variables within an ANN implemented in an R Studio environment. The methodological process involved the analysis of twenty years of archived maritime accident reports to identify and quantify the primary causal factors associated with vessel incidents. Spatial and aspatial datasets, including S-AIS vessel traffic density and multiple risk factor layers, were prepared and integrated. Each accident record was matched to the spatial values of these variables such as bathymetry, current velocity, CATZOC quality, and AtoN density, within its grid cell, thereby ensuring consistency in the model inputs. A predictive probability model was developed using a Multi-Layer Perceptron (MLP) ANN to simulate the relationships between the identified risk factors and the likelihood of maritime events. The model was applied across the Caribbean Sea to evaluate risk levels and identify potential hotspots for maritime eventss. Mitigation strategies were assessed by modifying the input variables to reflect the implementation of measures such as increasing AtoN, improving CATZOC quality, and reducing navigational hazards in high-risk zones. The ANN was retrained with the modified inputs, and the resulting predicted probabilities were compared to the baseline scenario to estimate reductions in incident risk.

4.3 Model development using ANN

Following the global comprehensive analysis of maritime accidents, 69 events occurred in the Caribbean Sea (Fig. 6), all involving vessels equipped with AIS at the time of the event. These events included 9 foundered events, 17 collisions, 13 contacts, 15 groundings, 8 fires/explosion, and 7 capsize events. To ensure accurate and unbiased predictions, the dataset was split into two subsets: 70 % for training and 30 % for testing. The training set was used to identify patterns and model the spatial structure of risk, while the testing set validated predictive accuracy. Each event location was spatially linked to the corresponding values of the identified risk factors using GIS-derived raster. The ANN was developed in R using the neuralnet package, adopting a Multi-Layer Perceptron (MLP) architecture configured as 9-5-1, nine input nodes for the explanatory variables identified in Section 4.0 (vessel density, bathymetry, hazard proximity, AtoN density, current velocity, CATZOC quality, chart age, vessel age, and flag state), five hidden neurons, and one output neuron. Five hidden neurons were selected after iterative testing of multiple configurations (3–7 neurons) and yielded the optimal balance between predictive accuracy and avoidance of overfitting. The chosen 1 km^2 spatial resolution provided sufficient granularity for regional-scale analysis without excessive computational load or AIS noise sensitivity.

A logistic activation function was applied to the hidden and output layers to enable nonlinear pattern detection while constraining outputs between 0 and 1, consistent with probabilistic risk estimation. The learning rate and weight initialization were tuned experimentally to minimize mean squared error during training, and all variables were normalized to a [0,1] scale to improve convergence stability. Training used forward–backward propagation. In the forward pass, input data moved through weighted connections and activation functions, producing increasingly abstract feature representations in the hidden layer before yielding a probability estimate in the output layer. Backpropagation then calculated prediction errors and propagated them backward through the network, adjusting weights according to error gradients. This process iterated over multiple epochs until predefined accuracy thresholds were met. By prioritising relatively stable variables (e.g., bathymetry, hazards, long-term traffic patterns) over short-term dynamic parameters, the model produces a baseline probabilistic risk surface for strategic planning rather than near-miss or real-time collision prediction. This differentiates it from operational timescale models and enhances its relevance for long-term maritime safety management in the Caribbean. The novelty of this work lies in synthesising underutilised hydrographic, environmental, and regulatory variables into a single probabilistic framework, yielding region-specific, actionable insights into navigational risk.

4.4 Model evaluation

A robust evaluation framework was employed to assess the ANN model's performance. Pairwise scatter plots were first used to visually examine relationships between each explanatory variable and the response variable. Generalized Weight Plots (GWP) were then generated to evaluate the independent contribution of each covariate, where high weight variance indicated

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nonlinearity. Sensitivity analysis using the Lek-profile method was applied to explore how changes in individual inputs affected predicted probabilities, verifying that the ANN was capturing real-world patterns. To further interpret model behavior, a Neural Interpretation Diagram (NID) and Garson's algorithm (1991) quantified and visualized the relative influence of each variable, revealing both direct and interactive effects. This combination of predictive modelling and interpretability techniques provided a transparent, objective, and rigorous approach to maritime risk assessment. By overcoming the limitations of traditional statistical models and removing subjective weighting, the ANN framework delivered data-driven probability estimates for open-sea incidents, supporting targeted mitigation strategies in the Caribbean Sea. The methodological framework for the probability model outlines the sequential process used to integrate data preparation, ANN model development, and evaluation procedures (Fig. 7).

5 Results

A hybrid evaluation and interpretability framework was implemented to rigorously assess the ANN and to elucidate the contribution of each predictor variable to maritime incident probability modelling. The framework integrates complementary statistical, graphical, and model decomposition techniques to address common challenges in neural network interpretability, including black-box opacity, nonlinear dependencies, and variable interaction effects. By combining correlation analysis, weight-based diagnostics, connection topology inspection, and perturbation-based sensitivity testing, the approach provides both global variable importance rankings and local behavioural insights.

The pairwise scatterplots and correlation coefficients, visualized in the heatmap (Fig. 8), provided an initial diagnostic of linear dependencies between predictors and the response variable, revealing relationships consistent with established maritime risk mechanisms. Strong positive correlations were observed between bathymetry and traffic density, AtoN density, and hazard proximity, indicating that shallow or constrained waters tend to concentrate vessel movements, require more navigational aids, and coincide with mapped hazards conditions commonly associated with grounding risk. AtoN density and hazard proximity were also strongly correlated, reflecting the clustering of navigational aids in hazardous zones, where their absence or malfunction could significantly increase risk. Similarly, CATZOC and survey age showed strong correlations with hazard proximity, underscoring the role of outdated or poor-quality charting as a latent risk factor. These patterns confirm that empirical variable relationships align closely with the ANN-predicted incident hotspots, reinforcing the model's grounding in real-world maritime safety dynamics.

NIDs further illuminated the ANN's decision-making process by visualizing the magnitude and polarity of connections from each input through the hidden layer to the output neuron. Thick positive-weight connections were identified for traffic density, vessel age, CATZOC, and hazard proximity, whereas less influential variables showed thinner or negative connections, indicating their comparatively smaller role in shaping predictions (Fig. 9).

Garson's algorithm decomposed network weights into normalized relative importance scores, producing a global ranking of predictor influence. Traffic density emerged as the most dominant factor, followed by navigational hazards, vessel age, current velocity, and chart quality. Minimal contributors, such as current

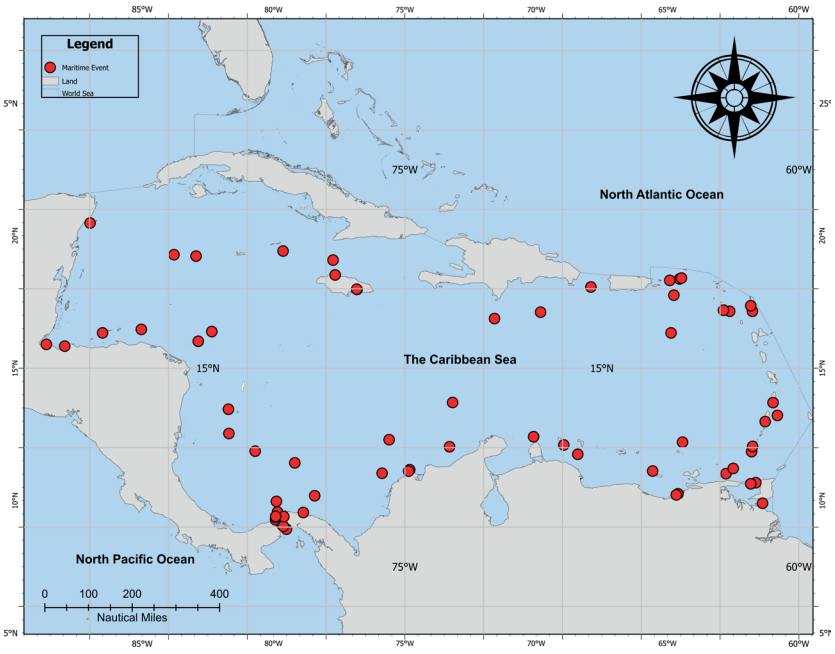


Fig. 6 Location of maritime events in the Caribbean Sea for the period of 2002–2021.

Preparation of Data
•RStudio Environment Setting •Preparation of Train and Testing Data
Compute Neural Net with Training Data
•Plotting of NN function network •Pairwise NN model results of Explanatory and
Variable Importance using NNET Package
•Compute NNET functon •Plot NNET function network •Variables Importance using NNET •Sensitivity Analysis of Expanatories and Response Data
Compute Neural Net fuunction for Prediction with Validation Data
•Prediction Validation results with AUC Value and ROC plots
Produce prediction map using Raster data
•Import and process thematic maps •Compute prediction function •Export final prediction map as raster.tif

Fig. 7 Methodological framework for probability model.

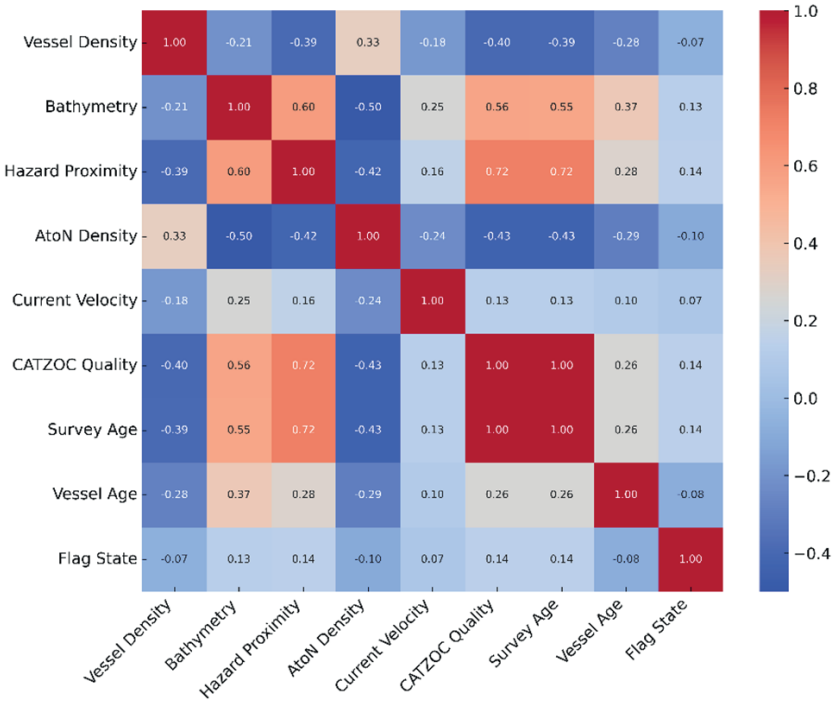


Fig. 8 Correlation heatmap of maritime risk factors and response variable.

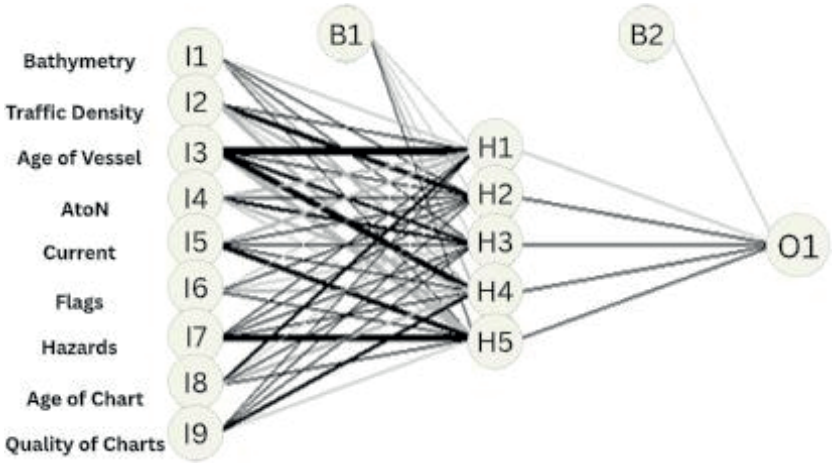


Fig. 9 NID showing variable influence pathways in ANN model.

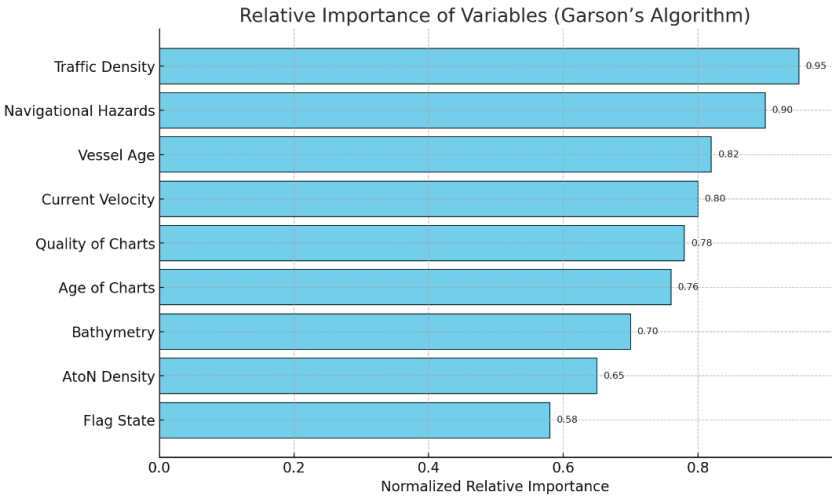


Fig. 10 Relative importance of risk factors derived using Garson's algorithm.

velocity and AtoN density, were retained in the model due to their potential interaction effects, as later confirmed through sensitivity testing (Figure 10).

Finally, model performance was assessed using Receiver Operating Characteristic (ROC) curves and Area Under the Curve (AUC) metrics. The ANN achieved perfect classification on the training dataset (AUC = 1.00) and 91 % accuracy on the independent test dataset (AUC = 0.91), demonstrating strong predictive skill and generalization with only a minor reduction in performance on unseen data (Fig. 11). The integration of these evaluation techniques provided a transparent, data-driven, and technically rigorous understanding of the ANN's predictive behavior, directly informing the prioritization of maritime risk factors for navigation safety planning in the Caribbean Sea.

5.1 Spatial analysis of predictive surface

The ANN model generated a raster-based probability surface highlighting spatial variation in maritime incident risk across the Caribbean Sea. The map revealed a range of prediction probabilities from low (0.0–0.3) to moderate (0.4–0.6) and high (0.6–1.0) with high-risk zones concentrated near busy port approaches, congested shipping corridors, and constrained areas (Fig. 12).

High-probability areas were pronounced in the approaches to major ports such as George Town (Cayman Islands), Belize City, Kingston (Jamaica), and the Panama Canal, reflecting the influence of vessel traffic density, outdated or poor-quality charting, navigational hazards, and high-risk flag states. For instance, Cuba's southern coast and port *Cienfuegos* and *Jucaro* showed very high predicted probabilities due to narrow channels, dense traffic, and charting deficiencies. Similarly, Belize's shallow docking limitations and high density of navigational hazards contributed to frequent groundings, confirming elevated risk levels in the ANN output. In the Gulf of Honduras, Puerto Cortes and Coxen Hole Island also emerged as risk-prone zones, reinforced by historical incidents, cargo volumes, and offshore supply traffic. The Panama Canal, a major global transhipment bottleneck, had the highest predicted probabilities, aligning with its global accident rate and concentration of Panamanian-flagged vessels often associated with poor safety oversight. Notably, open sea regions also exhibited high probabilities, suggesting that risk is not exclusive to coastal or port-adjacent waters. Events in these areas were primarily associated with collisions and onboard safety failures, indicating the need for increased navigational awareness even in deep-water zones. The Lesser Antilles showed extensive high-risk zones, especially near Port of Spain, Dominica, and Castries. This was attributed to dense cruise and cargo vessel activity, bathymetric constraints, and the presence of over 6,000 documented navigational hazards. The ANN model reinforced that vessel congestion, traffic type, and uncharted waters amplify the likelihood of accidents.

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Together, the ANN-derived probability surface offers a robust spatial representation of maritime risk across the Caribbean Sea. It validates key patterns observed in the historical accident database and confirms the role of multiple converging risk factors, such as traffic density, navigational hazards, port congestion, vessel flag and vessel type in shaping where future incidents are most likely to occur. The model's insights are vital for informing regional risk mitigation strategies and improving navigational safety.

5.2 Mitigation strategies for maritime navigation

To evaluate the effectiveness of risk mitigation strategies, specific improvements were applied to key causation factors within the ANN model. These included enhancements to Admiralty chart data (improving both quality and survey age), reduction of navigational hazards, ensuring proximity to functional AtoN, improvements in vessel registry safety (flag state), and replacement of older vessels with newer ones. For each variable, the improvement was implemented by modifying the corresponding raster layer used as ANN input: chart quality and survey age were adjusted to improved CATZOC categories; hazard density values were reduced; AtoN density was increased near major routes; flag state risk scores were reassigned to reflect higher safety compliance; and vessel age distributions were shifted toward newer vessels. These modifications were applied across the study area on a randomized but spatially consistent basis to simulate feasible, real-world improvements. The updated variables were reintroduced into the trained ANN model to predict new incident probabilities, allowing for direct comparison with the baseline scenario and quantification of the reduction in navigational risk.

The ANN was retrained using the improved datasets, and the resulting prediction surfaces were compared against the original model output. By subtracting the improved surfaces from the baseline probability map, the analysis quantified reductions in maritime risk as a function of each mitigation measure. This approach allowed for a spatially explicit assessment of how individual changes such as improved charting or an increase in AtoN could reduce the likelihood of maritime events. Unlike traditional assessments limited to confined waterways, this study addressed navigational risk at a regional scale, accounting for international waters across the Caribbean Sea. The findings underscore the importance of proactive mitigation strategies and their measurable impact on reducing risk, supporting informed decision-making for regional maritime safety enhancement.

5.2.1 Improvements to CATZOC

The CATZOC, which reflects the accuracy and reliability of Admiralty chart data, plays a critical role in maritime navigation safety. Most areas across the Caribbean Sea fall within lower-confidence categories (D and U), indicating inadequate or outdated surveys, particularly in open sea areas. In contrast, high confidence zones (A1 and A2) are typically limited to frequently dredged and surveyed port approaches. To assess the impact of improved hydrographic data, CATZOC categories were improved at random locations across the region, and the ANN model was retrained with these modified inputs. The results revealed a notable reduction in predicted maritime incident risk, particularly in high-traffic zones such as the Lesser Antilles, the Panama Canal, the southern coast of Cuba, and parts of Belize and Honduras. In several areas, predicted

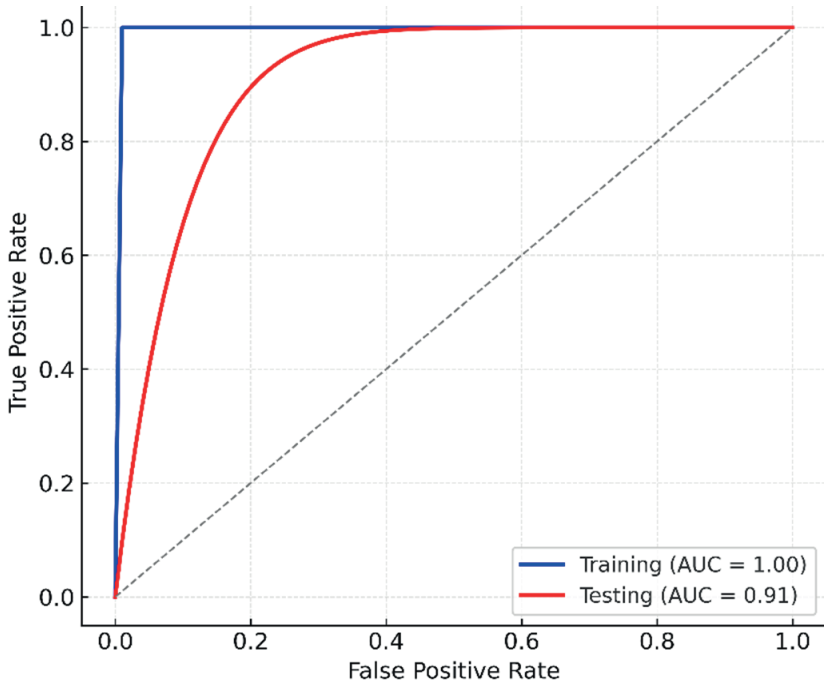


Fig. 11 ROC curve for ANN model performance.

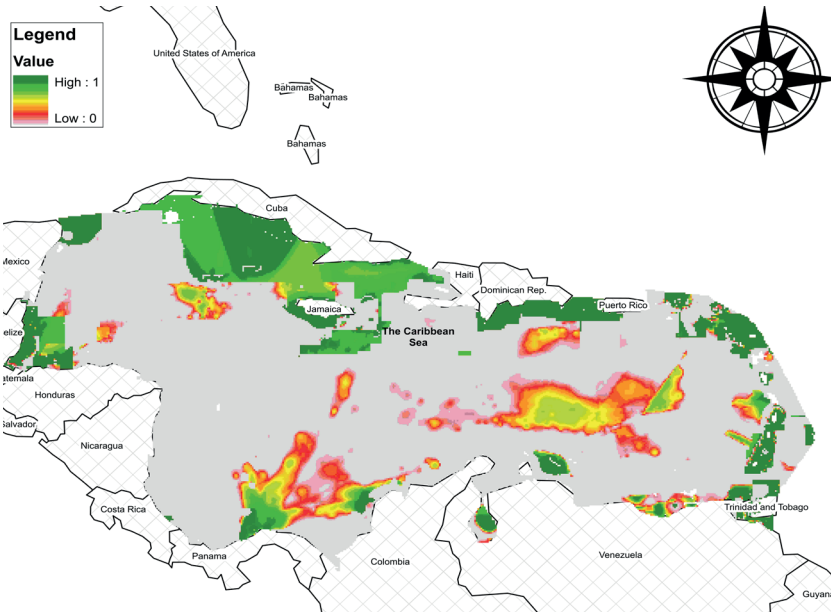


Fig. 12 Probability surface of the Caribbean Sea.

incident probabilities decreased from 0.8–1.0 to as low as 0.3–0.5, confirming that enhancing CATZOC data significantly reduces navigational risk (Fig. 13). This analysis highlights the importance of modern, accurate seabed surveys in improving maritime safety and supports prioritizing hydrographic efforts in poorly charted regions.

5.2.2 Improvements to navigational hazards

Outdated hydrographic surveys and sediment shifts on the seafloor have contributed to the accumulation of numerous navigational hazards in the Caribbean Sea, including reefs, wrecks, rocks, pipelines, and foul grounds. These hazards pose significant threats to maritime safety, especially when located near key shipping lanes or densely trafficked port approaches. It is important to note that while the ANN model was trained and tested using 69 maritime events from the Caribbean Sea. The navigational hazard layer used as one of the input variables was sourced from UKHO data, which contains 9,404 documented hazard locations across the entire study area. To evaluate the potential impact of hazard reduction, approximately 2,000 of these hazard points were randomly removed from the hazard layer, and the modified dataset was used to retrain the ANN model. The retrained model was re-evaluated using ROC, AUC, and classification accuracy metrics, which confirmed performance levels comparable to the baseline model, indicating that the scenario modification did not compromise predictive capability. The updated prediction surface showed a substantial reduction in maritime incident probability, particularly across high-traffic regions such as the Lesser and Greater Antilles, Jamaica, the Panama Canal entrances, northern Honduras, and northeast Venezuela. In some open sea areas west of the Lesser Antilles, predicted risk values decreased between 0.1 and 0.3 (Fig. 14). This result demonstrates that decreasing the density of navigational hazards either through improved charting, hazard removal, or better hazard management can meaningfully reduce the probability of maritime incidents in high-risk zones.

5.2.3 Improvements to AtoN

AtoN including buoys, beacons, lighthouses, and lights are vital for guiding vessels safely through confined channels, port approaches, and offshore areas. These systems assist mariners in avoiding hazards and maintaining accurate bearings, especially where natural landmarks are absent. However, their effectiveness can diminish due to environmental conditions, poor maintenance, or drifting, which poses significant risks to maritime safety. Despite global oversight from the IALA, several limitations remain, including limited regional coverage, resource constraints, and a lack of regional enforcement power. As a result, mariners often rely on multiple navigation methods alongside AtoN, particularly in high-risk or poorly monitored areas. To assess risk reduction, the number of AtoN was increased across the Caribbean Sea by adding more locations along channels, port approaches,

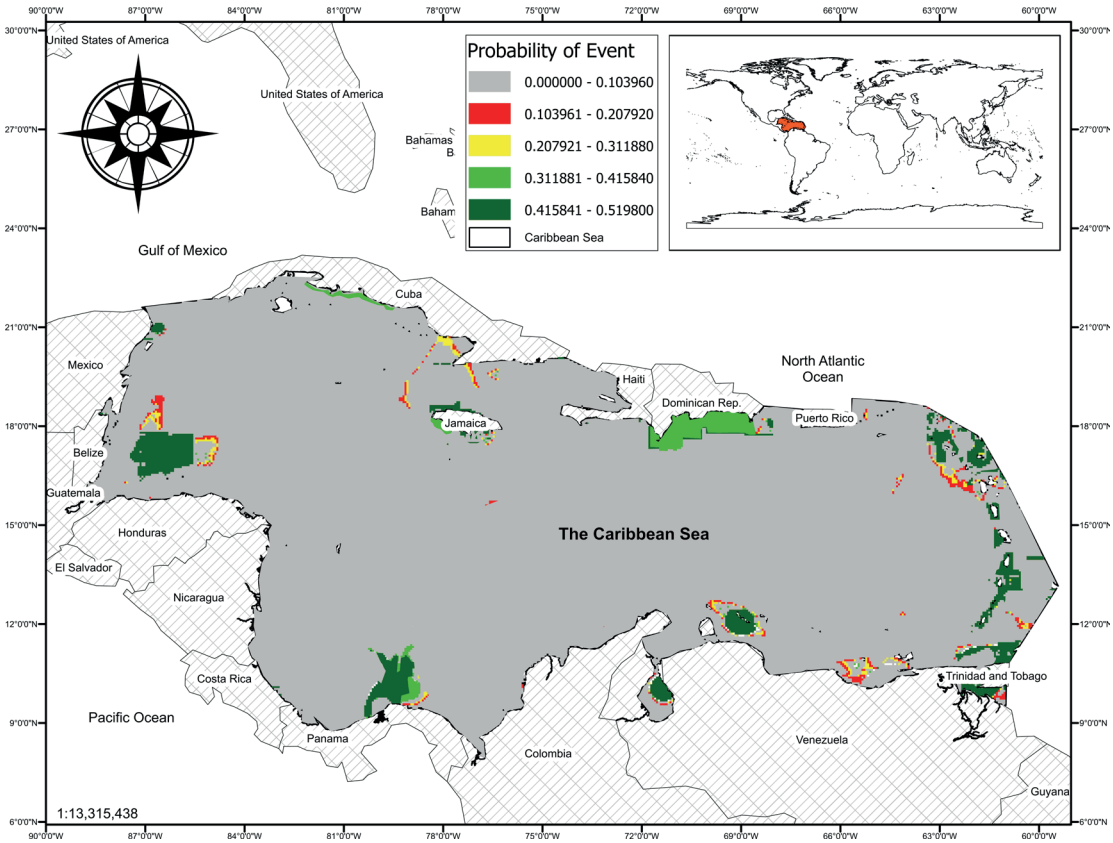


Fig. 13 Improvements due to CATZOC probability surface.

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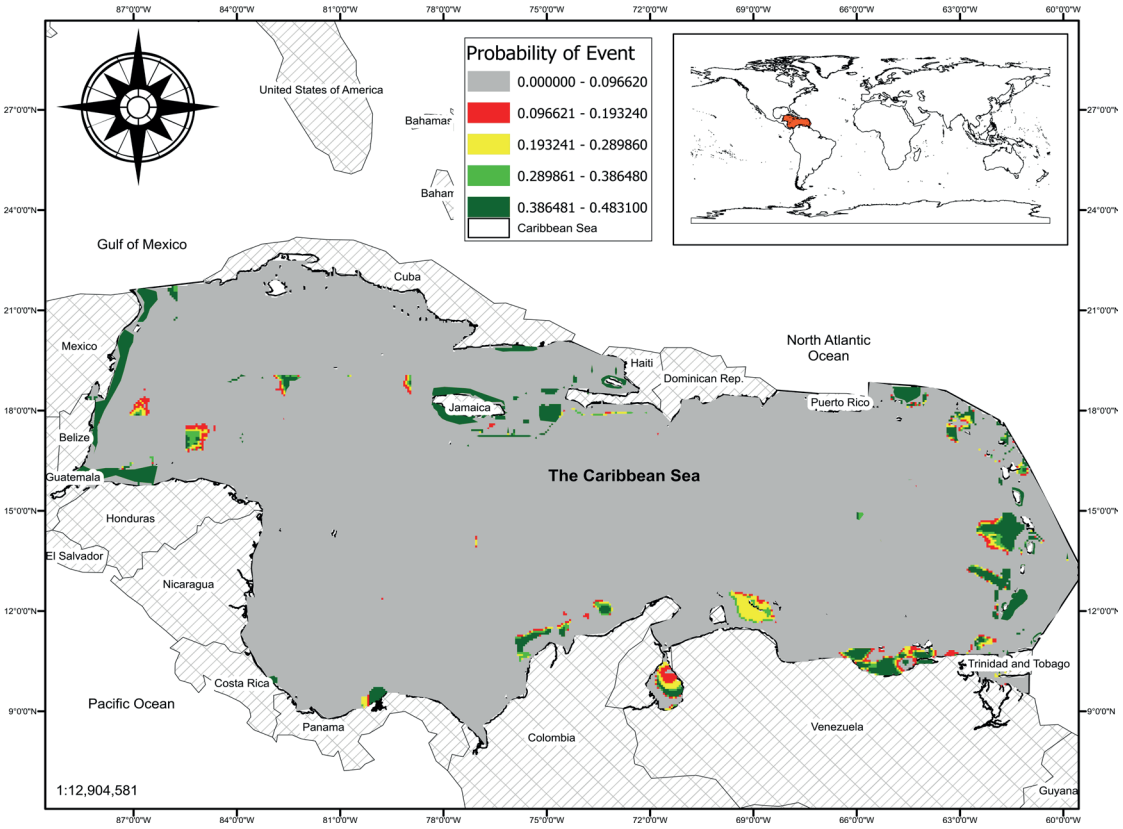


Fig. 14 Improvements due to navigational hazards probability surface.

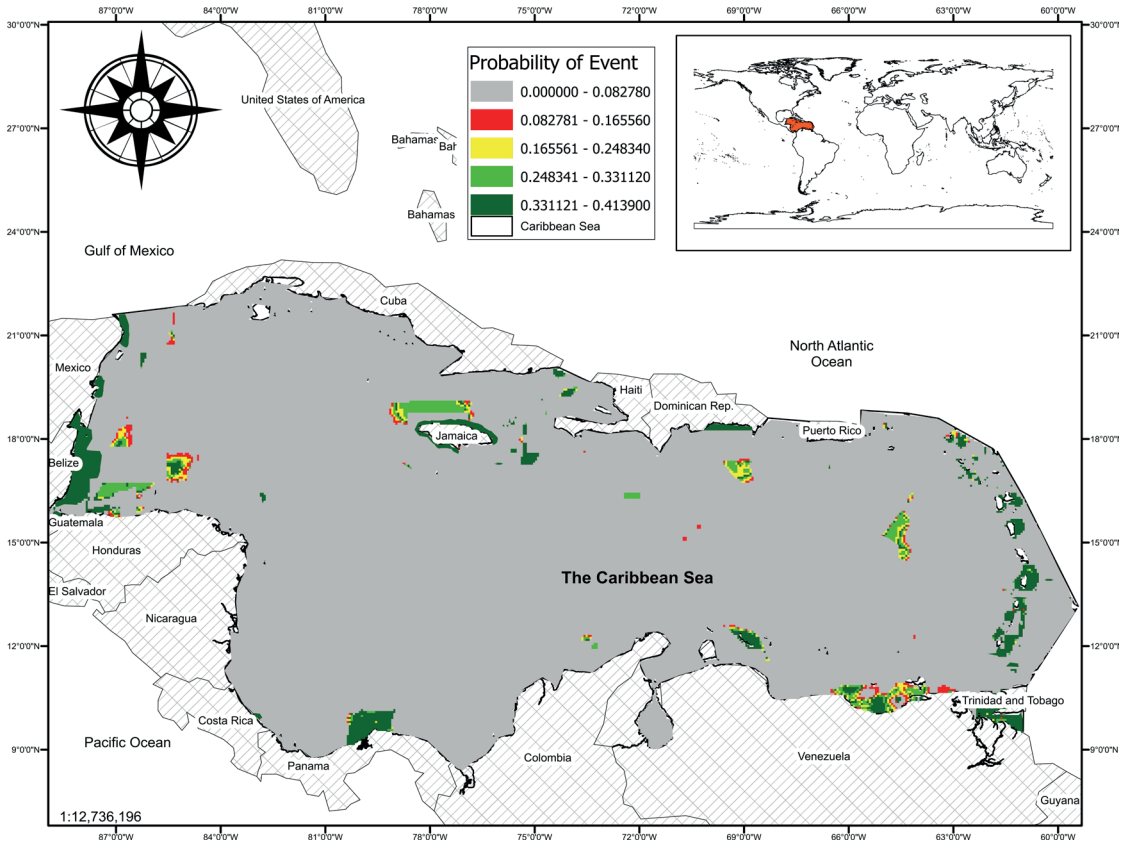


Fig. 15 Improvements to AtoN probability surface.

and high-traffic offshore areas. The ANN model was then retrained with the updated AtoN dataset. This improvement led to a notable reduction in accident probability, particularly within the port approaches of the Greater and Lesser Antilles, Southern Cuba, the Dominican Republic, Panama Canal entrances, and coastal waters near Belize and Honduras. In many of these areas, predicted accident probabilities decreased from 0.8 to as low as 0.2 (Fig. 15). These results underscore the importance of maintaining and expanding AtoN infrastructure as a practical and impactful mitigation strategy for improving maritime safety in the region.

5.3 Evaluation of mitigation strategies

The effectiveness of the proposed mitigation strategies was evaluated through a detailed examination of historical maritime accident reports. This assessment involved comparing the spatial and causal characteristics of past incidents with the areas and variables targeted for improvement within the risk model. By aligning reductions in predicted risk with documented causes of accidents such as outdated charting, insufficient AtoN, and navigational hazards the study validated that the improvements addressed real-world vulnerabilities within the Caribbean Sea maritime domain. This comparative analysis helped to determine the associated long-term benefits of each mitigation strategy. Key outcomes included the potential to significantly reduce pollution events, loss of life, and vessel damage through proactive interventions such as updated bathymetric data, enhanced AtoN, and modernization of vessel fleets. The reductions in risk observed across port approaches and open sea areas especially where historical events had occurred provided strong evidence of the accuracy and practical value of the mitigation strategies adopted. These findings support their application in broader maritime safety planning and underscore their role in fostering a safer and more resilient navigation environment throughout the Caribbean Sea.

5.3.1 Evaluation of CATZOC and survey age risk reduction measures

To assess the effectiveness of improvements made to the CATZOC and survey age, three main types of maritime events; collisions, contacts, and groundings were analysed in relation to the improved risk surface. The findings revealed that a majority of these events occurred in poorly surveyed areas (CATZOC D and U), particularly at night when visibility is limited, and vessel manoeuvrability is reduced. Collision and contact events were concentrated near the entrances of the Panama Canal and the Lesser Antilles, often compounded by ineffective or missing AtoN. Grounding events, primarily involving cargoes, tankers, and container vessels, were found in high-traffic zones like Jamaica's northern coast, the Panama Canal approaches, and east of Belize regions previously identified as high risk due to inadequate survey coverage. Following improvements to CATZOC in these critical areas, the risk probability significantly decreased, with model outputs showing a reduction in likelihood to approximately 0.4 (Fig. 16). These results validate the CATZOC improvement as an effective mitigation strategy, particularly for reducing risk in port approaches and high-density navigational corridors across the Caribbean Sea.

5.3.2 Evaluation of mechanical failure due to aged vessels

The analysis found that vessels between 17 and 37 years of age were significantly more prone to mechanical failure, contributing to a high number of maritime events. Globally, vessels built between 1984 and 2004 contributed to most accidents, with similar patterns observed in the Caribbean Sea, where 29 incidents involved aged ships. Specifically, seven mechanical failure incidents attributed to the aging of a vessel occurred in high-risk areas such as the entrances to the Panama Canal, the northern coast of Venezuela, and open sea regions. These seven cases consisted of 2 collisions, 2 groundings, 1 fire/explosion, and 2 contact events. This distribution highlights that mechanical failures in aged vessels can manifest in multiple accident types, reinforcing their role as a critical underlying risk factor. Following targeted improvements to reduce the presence of aged vessels in the maritime domain, the ANN model was retrained with the modified dataset. The results showed a significant decrease in incident probability in these zones (Fig. 17). The risk map depicts a reduced likelihood of occurrence to 0.2, confirming that replacing or upgrading older vessels is an effective mitigation strategy for enhancing maritime safety.

5.3.3 Evaluation of collision and groundings with improved AtoN

Over the 20-year period, 69 maritime events occurred in the Caribbean Sea, with 11 collisions and 16 groundings being the most common, primarily involving cargo, tanker, fishing, and container vessels. These events often occurred at night due to limited visibility and manoeuvrability, particularly in areas without effective AtoN. To evaluate the potential benefits of enhancing navigational aids, a modified AtoN layer in which the number of AtoN was increased, particularly near port approaches across the Greater and Lesser Antilles and is assumed to be fully operational. This modified layer replaced the original AtoN input in the ANN model, which was then used to generate a new prediction surface. The resulting output (Fig. 18) shows the simulated reduction in incident probability compared to the baseline, with risk in previously high-incident areas decreasing to approximately 0.4. This indicates that strategic increases in functional AtoN could substantially improve navigational safety, especially in collision- and grounding-prone zones.

This section evaluated a series of mitigation measures aimed at reducing maritime navigation risk

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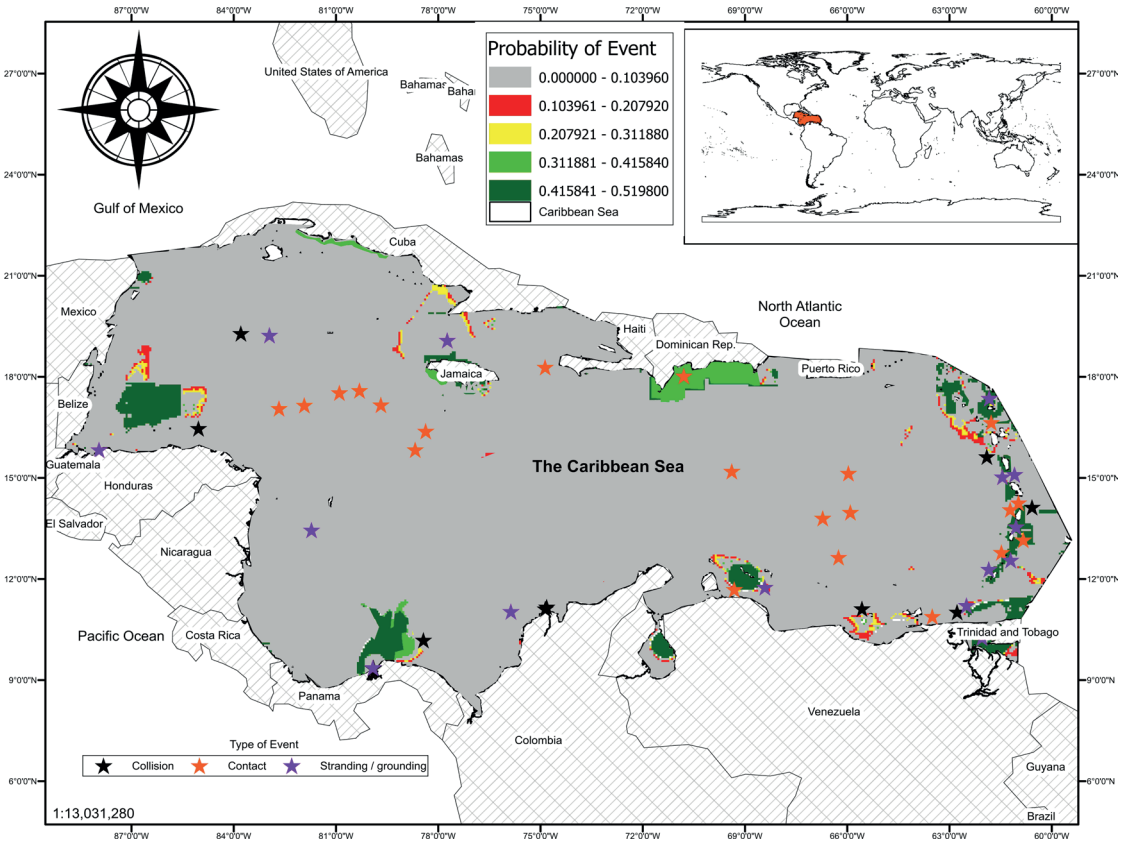


Fig. 16 Maritime accidents with CATZOC improvements probability surface.

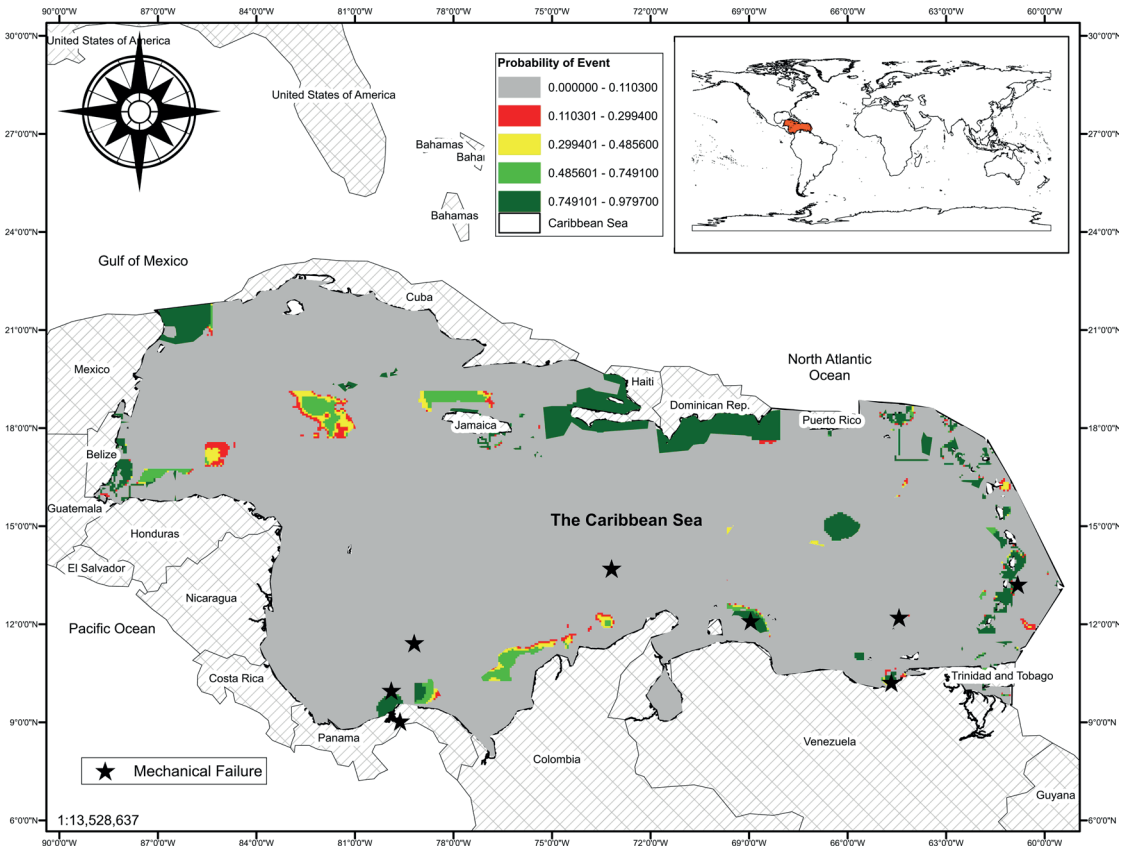


Fig. 17 Location of mechanical failure events superimposed on improved aged vessels probability surface.

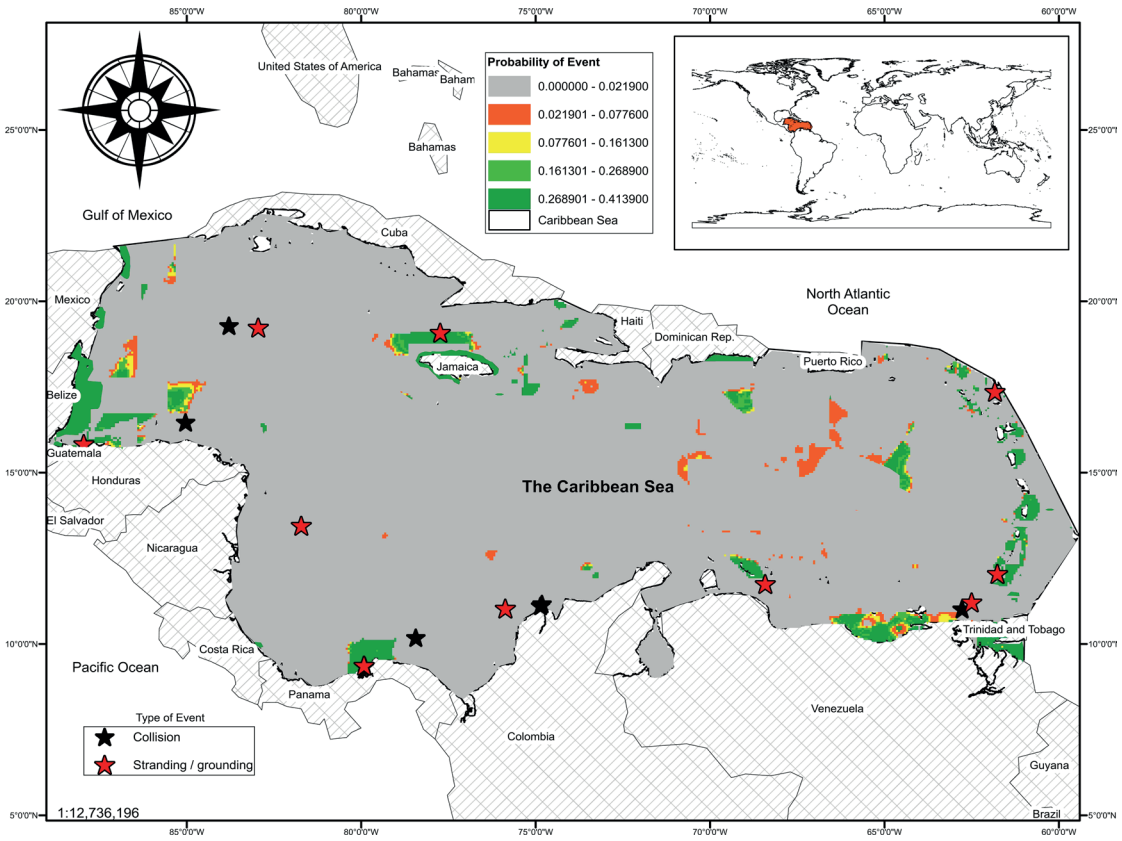


Fig. 18 Collision and groundings events with improved AtoN probability surface.

across the Caribbean Sea. Improvements to key causation factors such as updated charting, AtoN, navigational hazard reduction, vessel flag, vessel age, CATZOC classification were applied as part of a comprehensive traffic management strategy. Using ANN and consistent vessel traffic data derived from AIS, simulated testing demonstrated the effectiveness of these measures. The analysis revealed significant risk reductions across the region, with notable improvements in high-risk areas. Overall, the findings underscore the value of targeted mitigation strategies in improving navigational safety and support the continued use of data-driven approaches to guide maritime risk management in the Caribbean.

6 Conclusion

This study introduced a novel, data-driven risk assessment strategy for maritime navigation in the Caribbean Sea, leveraging ANN and a wide array of contributory variables. Unlike traditional hydrographic risk assessments that are typically confined to specific waterways, this research expanded the scope to open seas and regional contexts. It integrated geospatial data, historical maritime accident records, and satellite AIS data to develop a probability model capable of predicting high-risk locations for maritime events. The research began by identifying key causal factors influencing maritime accidents, including traffic density, bathymetry, velocity of current, vessel age, flag state, navigational hazards, chart quality and age and AtoN. Using ANN, the model was trained and validated with over 20 years of accident data, achieving a high prediction accuracy of 91 %. The ANN model not only predicted accident likelihood but also provided interpretability through techniques such as generalized weight plots, sensitivity analysis, and Garson's algorithm. The probability surface revealed key high-risk regions, including the entrances to the Panama Canal, port approaches of Jamaica and the Lesser Antilles, and open sea areas driven by dense traffic, outdated surveys, poor chart quality, and aged vessels. Mitigation strategies were tested by improving individual causation factors, such as updating charting data, reducing navigational hazards, increasing AtoN, and enhancing vessel safety by flag state and vessel age. Simulation of these mitigation scenarios showed significant risk reductions, particularly near major ports and transhipment corridors. The CATZOC improvements alone halved the probability of events in several high-risk areas. Evaluations of events such as collisions, groundings, and mechanical failures validated these reductions, confirming the effectiveness of the mitigation strategies. Importantly, this paper demonstrated the applicability of ANN for maritime risk assessment at a regional scale. The methodology enables prioritization of hydrographic surveys, supports decision-making for maritime authorities, and provides a foundation for future Vessel Traffic Services (VTS) or Traffic Separation Schemes (TSS) across the Caribbean Sea. The study offers actionable insights for enhancing maritime safety, reducing environmental impacts, and informing regional marine traffic

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management in support of sustainable development.

While this study demonstrates the potential of ANNs for regional maritime risk assessment, it is not without limitations. The integration of datasets compiled across different time periods, the reliance on a standard 70:30 training-to-test data ratio, and the use of simulated adjustments in mitigation scenarios all reflect necessary assumptions. These assumptions, though common in data driven modelling, may introduce uncertainties when applied to real-world operations. Nonetheless, the framework developed here provides a transparent and adaptable foundation for prioritizing hydrographic surveys, guiding maritime authorities, and evaluating future safety interventions as more harmonized and comprehensive datasets become available.

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Michael Sutherland

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