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Spatial Analysis of Maritime Disasters in the Philippines: Distribution Patterns and Identification of High-Risk Areas

Glenn D. Aguilar [1,*], Yasmin P. Tirol [2], Ryan M. Basina [2] and Jamaica Alcedo [2]

1 School of Environmental and Animal Sciences, Unitec Institute of Technology, Auckland 1025, New Zealand
2 College of Fisheries and Marine Sciences, Aklan State University, New Washington 5610, Philippines; yhptirol@asu.edu.ph (Y.P.T.); rbasina@asu.edu.ph (R.M.B.); jmalcedol@asu.edu.ph (J.A.)
* Correspondence: gaguilar@unitec.ac.nz

Abstract: Maritime accidents frequently occur in the Philippine archipelagic waters, often resulting in significant loss of life. These incidents highlight the urgent need for improvements in the country's maritime safety systems. By utilising accident data from the Philippine Coast Guard and the GISIS IMO databases, spatial analytical approaches were employed to determine incident distribution patterns and resulted in an overall depiction of the likelihood component of risk across the country's territorial waters. Kernel density and hotspot analysis revealed areas where incidents were concentrated and where statistically significant hotspots occurred. The Maxent tool was used to develop risk likelihood models for the incident locations using environmental rasters representing wind speed, significant wave height, depth, surface current, land distance and port distance. Model performance metrics including the AUC, TSS and Kappa were used to compare the two datasets and provide confidence on model robustness. Variable contribution figures showed that land distance is the most influential variable, with the majority of high-risk areas predominantly located near population centres. The resulting maps provide an intuitive and informative depiction of the characteristic patterns of maritime accidents in the country, identify areas of high risk requiring immediate attention and offer valuable insights to support strategies for improving and enhancing the country's maritime safety.

Keywords: maritime accidents; disasters at sea; Philippine waters; safety at sea; risk analysis

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1. Introduction

The territorial waters of the Philippine archipelago are known for some of the worst maritime disasters outside of major conflicts or periods of war [1]. In East Asia, the Philippines recorded the highest absolute casualty rate between 2000 and 2012, 40% higher than second-ranked Indonesia. The country also ranked first for casualties, with 0.118 per total fleet size, compared to 0.033 for both Indonesia and Vietnam [2]. The highest recorded passenger deaths resulted from the *Dona Paz* incident in 1987, with estimated reports of 4386 casualties [3–5]. From 2015 to 2020, the Philippine Coast Guard recorded 4467 maritime accidents in Philippine waters [3]. Recent incidents with multiple fatalities were due to capsizing [6], fires onboard [7], and collisions [8], with capsizing reported as the most prevalent type of accident [9]. These incidents are attributed to a combination of recurring typhoons, inadequacies in the country's maritime infrastructure, and issues in governance and management systems, which remain areas of concern [10].

Globally, most accidents occur within sight of shore or near coastlines, with the Philippines, China, Japan, South Korea and Vietnam having hotspots of accidents within their coastal waters [11]. Areas in the vicinity of major ports and large population coastal cities had most of the casualties reported in the United States [12]. The nature of the incidents requires knowledge derived from spatial analysis of maritime accident data using appropriate modelling approaches to support projects and strategies for an improved safety infrastructure. Such systems must complement appropriate training of crew, vessel traffic systems, route planning software and well-implemented management systems together with good governance, particularly in the Philippines [13]. A systematic, spatially based approach to risk assessment, not only of maritime incidents but all aspects of the industry, is seen as relevant in several international efforts on safety at sea [14–16].

Maritime risk analysis is an important component supporting international and national agencies in charge of safety of life at sea [14]. The complexity presented by the combination of human factors, vessel characteristics and environmental conditions necessitates the development of models based on incident data and related variables that serve as the basis for risk assessment [17]. The IMO's recommendation to use a proactive safety approach through the Formal Safey Assessment [18] signals the importance of concerted efforts to develop relevant computational approaches, applications and systems to provide tools for maritime risk analysis. From the solutions provider or researcher side, the rapid growth in the number of publications that mention or use the worldwide data of vessel location provided by the global Automatic Identification System (AIS) supports the growing interest in developing solutions for addressing maritime accidents [19].

Geographic Information Systems (GIS) provide the tools and platform to process spatial information and analyse relationships, even from incomplete information in a complex environment [20]. Some related studies pinpoint high-risk areas for the maritime territories of Malaysia [21], Korea [22], the United States [23] and worldwide [24]. Marine-related aspects of developing or applying GIS applications include planning and implementing maritime search and rescue [25,26], piracy risk assessment [27,28] and oil spill emergencies [29].

GIS-based approaches to accident analysis typically utilise cell- or grid-based locations alongside contributing factors such as vessel routes, traffic volume and ship types [23]. Analytical tools employed in these studies include kernel density [21], hotspot analysis [20,24], fuzzy analytic hierarchy technique [30] and other machine learning approaches, including Support Vector Machines and Random Forest [31]. For this study, Maxent [32] was selected to model the risks associated with recorded incidents and specific environmental variables. While most uses of Maxent were for Species Distribution Modelling (SDM) for finding the suitability of areas of a particular species using their occurrences and a set of environmental variables [33–35], it has also been applied to a variety of other distribution modelling research that seeks to provide predictive maps classifying areas according to a range of values representing risk, susceptibility, vulnerability or other measures needed for decision support. Maxent requires two sets of data, the location of species and the environmental variables where the species are located. Instead of species occurrences, incident location data is used for the model. Implementation of Maxent outside of the suitability modelling of species has included determining area susceptibility to wildfires in Turkey [36], urban water logging risk assessment in Tianjin, China [37], landslides in Nepal [38], flooding from hurricane Harvey in Texas [39], typhoon damage in Davao, Philippines [40] and agricultural drought in India [41]. For marine and maritime research, Maxent has been used to evaluate suitable shipping paths in the Malacca Strait [42], assess vulnerability of mangrove areas in Mozambique [43] and map night-time fishing activities in the Philippines [44].

This study characterises the spatial patterns of maritime incidents in the Philippine archipelago to provide quantitative estimates of the likelihood component of risk assessment. It aims to contribute to the application of geospatial tools and methodologies in a region where the published literature is sparse and research on this specific focus and methodology remains limited. By combining a grid-based approach and geostatistical tools such as kernel density and hotspot analysis, together with the machine learning tool Maxent, this study provides a means of cross-checking outputs across tools to enhance confidence in the results. This novel approach strengthens the reliability of the final risk-mapping output. More importantly, the resulting map products are designed to contribute to the knowledge base required for improved maritime safety in the Philippines.

2. Materials and Methods

Maritime incident data from available sources include records from the Philippine Coast Guard (PCG) covering the years 1995–2000 [1] and the Global Integration Shipping Information System (GISIS) hosted by the International Maritime Organisation (IMO) from 2001–2020 [45]. In cases where geographic coordinates were not explicitly available, the names of places from the reports describing the vicinity of the incident were used as input for the Geocoding tool in ArcGIS Pro. The resulting coordinates were verified manually in Google maps with reference to well-known routes and adjusted for accuracy and consistency. News media reports on the incidents were another source of information to cross-check the coordinates. The PCG data included all incidents reported to the various Coast Guard districts and included a significant number of bancas or native outrigger boats that make up the majority of seacraft in the country [9]. The IMO database, on the other hand, does not include such small boats but reflects incidents reported by national bodies according to IMO requirements [3]. This difference in data sources required the analysis and modelling of both data sets to show the distribution patterns and the results of the different tools used in the analysis.

The area covered includes waters 12 nautical miles from an archipelagic baseline as formally defined by the Philippines [46,47]. The archipelagic boundary was sourced from the geoportal website (https://www.geoportal.gov.ph/ (accessed on 1 January 2022) with the buffer zone of 12 nautical miles added in ArcGIS Pro. The resulting territorial waters were then subdivided into a hexagon grid set at 100 square kilometers each to provide a systematic basis and facilitate the geostatistical analysis. The hexagonal grid was selected because of its ability to cover complex shapes, compact topology and uniform adjacency amongst neighbouring cells [15]. The hexagon grids provide more consistent cell areas, better symmetry with nearest neighbours as well as low perimeter-to-area ratio that contributes to more accurate results for spatial statistical tools [48]. In terms of visualisation, there is lesser ambiguity at the edges compared to rectangular grids [49]. A uniformly sized grid was recognised as a convenient and useful integrative approach to maritime risk assessment involving multiple datasets and machine learning tools [15]. Similar grid-based approaches were used to identify high-risk areas in the UK [50], to assess Southwest Pacific hydrography risk [51] and to enable global coverage of maritime incidents [15].

The kernel density tool in ArcGIS Pro [52] was used to describe the spatial distribution of the locations of incidents and provide a visualisation of the magnitude per unit area of the original incident locations. Default values for the tool were used for this analysis. The use of the tool in this study is based on its robust depiction of incident distribution as reported on related work to characterise and identify high-risk maritime locations in Malaysian waters [21], fishing and maritime traffic incidents in the Atlantic waters of Canada [53], incidents in Fujian Province of China [54] as well as global patterns of maritime accidents [25]. The optimised hotspot tool [55] was used to determine the pattern of distribution based on the Getis Ord Gi* statistic [56] and produces a map depicting significant hotspots and coldspots of variables for incident location. The optimised hotspot tool of ArcGIS Pro produces z-scores with corresponding *p*-values to determine the coldspot or hotspot significance of the feature. The confidence level (Gi bin) is the default symbol of the output map that conveniently categorises the features with values ranging from significant coldspots to hotspots, at 99%, 95% and 90% levels of confidence.

Maxent was selected as the most appropriate tool due to its capability to use presence-only data, robust model outputs and applicability to a wide range of domains [32,37,38]. We developed two Maxent models, one for each dataset, depicting areas with the greatest probability of incidents translated into determination of risk over archipelagic waters of the Philippines. The inputs for Maxent were the location of the centroids representing rarefied occurrence data to address spatial autocorrelation [57]. Relevant environmental factors were selected including bathymetry or depth, land distance, port distance, wind speed, surface current velocity and wave height [58]. Rasters were downloaded from the GMED database and clipped to the Philippine archipelagic waters [59]. Maxent then uses the values of these variables at the locations of the incidents to develop the model. To test for redundancy, environmental factors were tested for cross-correlation at Pearson coefficient correlation values of 0.6, 0.7, 0.8 and 0.9 using the SDM Toolbox [60]. Variables with coefficient correlation less than or equal to 0.7 were used in the modelling. Maxent parameters to evaluate performance include turning on Random Seed and the test percentage to 20%, using subsample for the replicate type and setting the maximum iterations to 10,000. There were no threshold rule sets for the modelling.

The models resulting from the two datasets were evaluated according to Area Under the Curve (AUC) of the Receiving Operator Characteristic, Kappa and True Skills Statistic (TSS) [61,62]. The AUC is a commonly used measure of model performance that provides an indication of accuracy predicting presence and absence. A resulting AUC value greater than 0.7 indicates good model performance [63]. To further evaluate the model, the Kappa and TSS statistics were also employed. The Kappa statistic value is a measure of the agreement between the observations and predictions and includes the effect of chance prediction accuracy with values nearing 1.0 showing good performance [38,63]. The TSS compensates for weaknesses observed in Kappa, particularly its sensitivity to prevalence. Values of the TSS near 1.0 indicate good performance [64]. Values of Kappa and the TSS were determined using a script in r that uses as inputs the results of the Maxent model.

3. Results

3.1. Locations of Maritime Incidents

Incident locations were mainly around the major ports such as Manila, Cebu and Iloilo (Figure 1). Clusters of incidents were near land or shore for both datasets. When counts were presented in the hexagonal grid generated, the GISIS recorded data show far fewer incidents over Philippine waters, a reflection of the coverage reported for the country.

3.2. Density and Hotspots

Kernel density analysis shows similar areas with high intensities of incidents, with a high concentration just off the central Visayan island of Cebu, where significant shipping activity occurs close to major population centres (Figure 2).

Hotspot analysis maps display a distribution of incidents similar to kernel density results, with significant hotspots shown in central Cebu and Manila for both datasets, while a hotspot is shown in the waters between Mindoro and Batangas, a major shipping route (Figure 3).

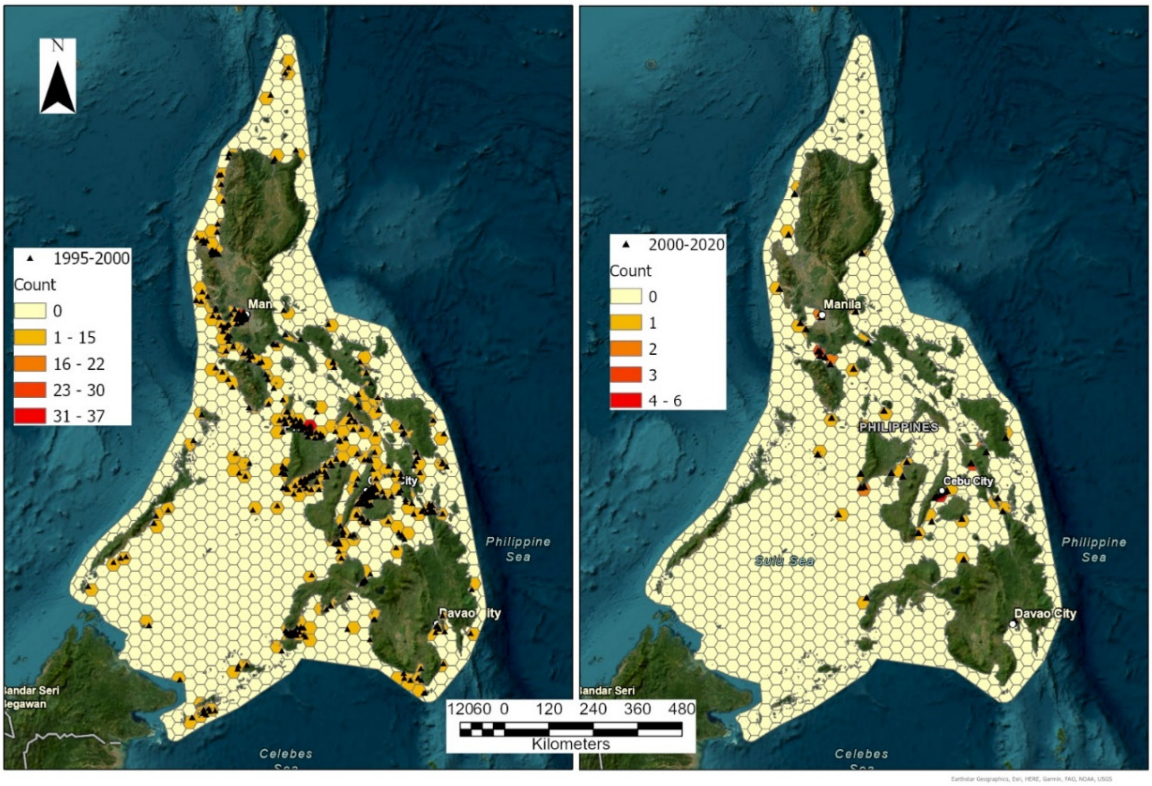


Figure 1. Incidents recorded from 1995–2020 with a hexagon grid for spatial analysis for PCG (**left**) and GISIS (**right**) data.

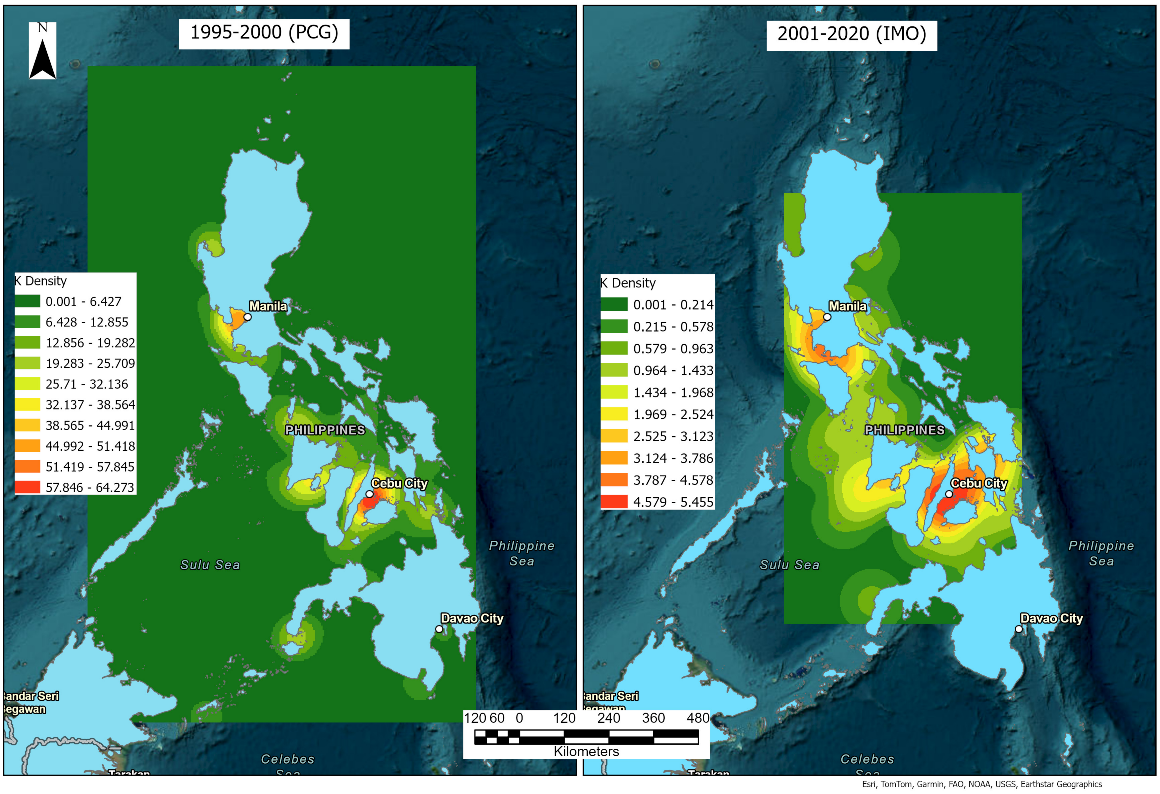


Figure 2. Kernel density of incident data from the PCG 1995–2000 (**left**) and GISIS 2001–2020 (**right**).

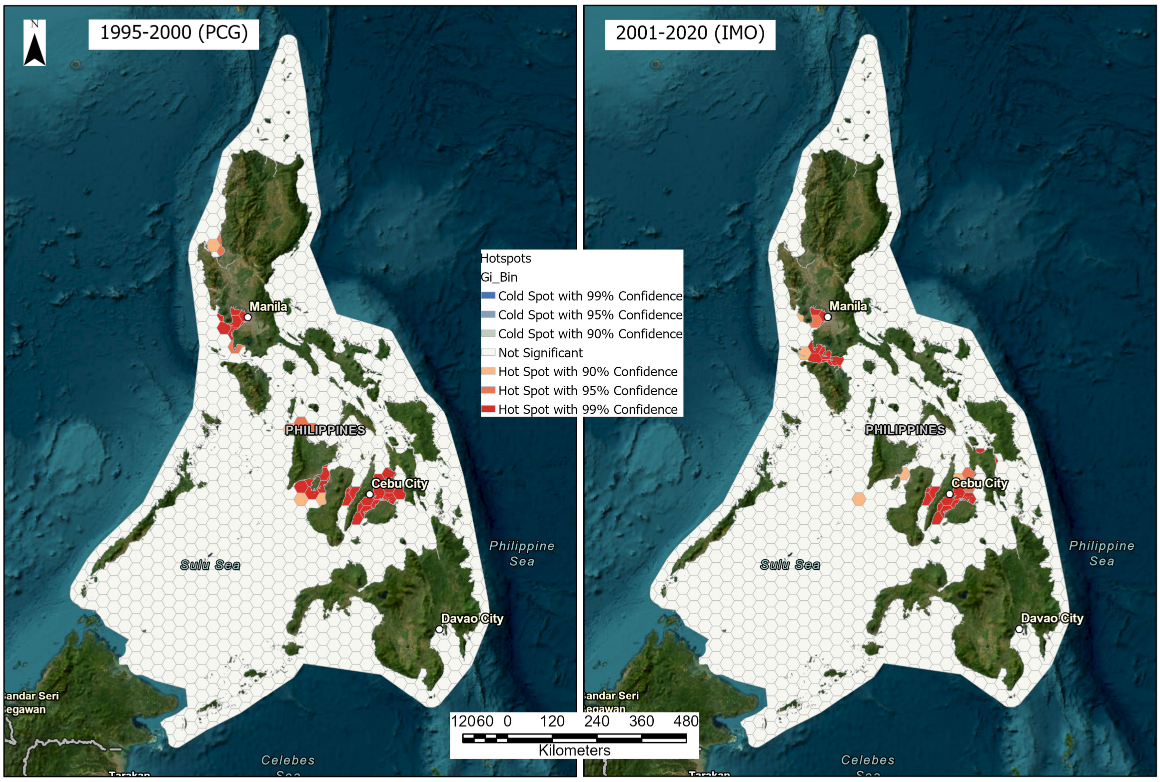


Figure 3. Results of optimised hotspot analysis for PCG data (**left**) and GISIS data (**right**).

3.3. Incident Distribution Modelling

When the environmental variables wind speed, wave height, surface current, depth, land distance and port distance used in Maxent were tested for cross-correlation, variable pairs showed correlation coefficients less than 0.70. This signifies variable independence, allowing their use in Maxent modelling. Annual average wind speed is highest in the northernmost part of the archipelago, while lower wind speeds are observed between islands or in internal waters. Wave height is significantly greater in the eastern side facing the Pacific Ocean, while lower values occur within the archipelago. The port distance raster is a measure of distances from the major ports of the country, whereas land distance is measured from the shoreline of each island. (Figure 4).

Results of the Maxent model show the high-risk areas near land and major ports of the country (Figure 5). This is consistent with the results of the kernel density and hotspot tools, with other additional areas highlighted. Most of the high-risk areas identified in the model are near large population centres with busy shipping traffic or fishing activities. The results of Maxent modelling are similar for the two datasets in terms of the high-risk and low-risk area indications.

In terms of variable contribution to the model, land distance made the highest contribution to the test model, followed by port distance and wind speed. This reflects the nature of most accidents, which occur near landmasses and busy ports. The values of each variable that have the most impact on the model are depicted in Figure 6. For depth, the model shows that shallower areas have the greatest effect on results for both the PCG and GISIS data, with deeper areas having pronounced influence on the GISIS data. The response curve of the variables land distance and port distance on the Maxent model are similar for both datasets, with closer distances having a greater influence. Surface current effects show peak responses at a similar range of current velocity values. However, wave height responses differ between datasets, with the PCG dataset peaking at greater wave heights than the GISIS dataset. Wind speed likewise shows differences in the peaks and the shape of the response curves (Figure 6).

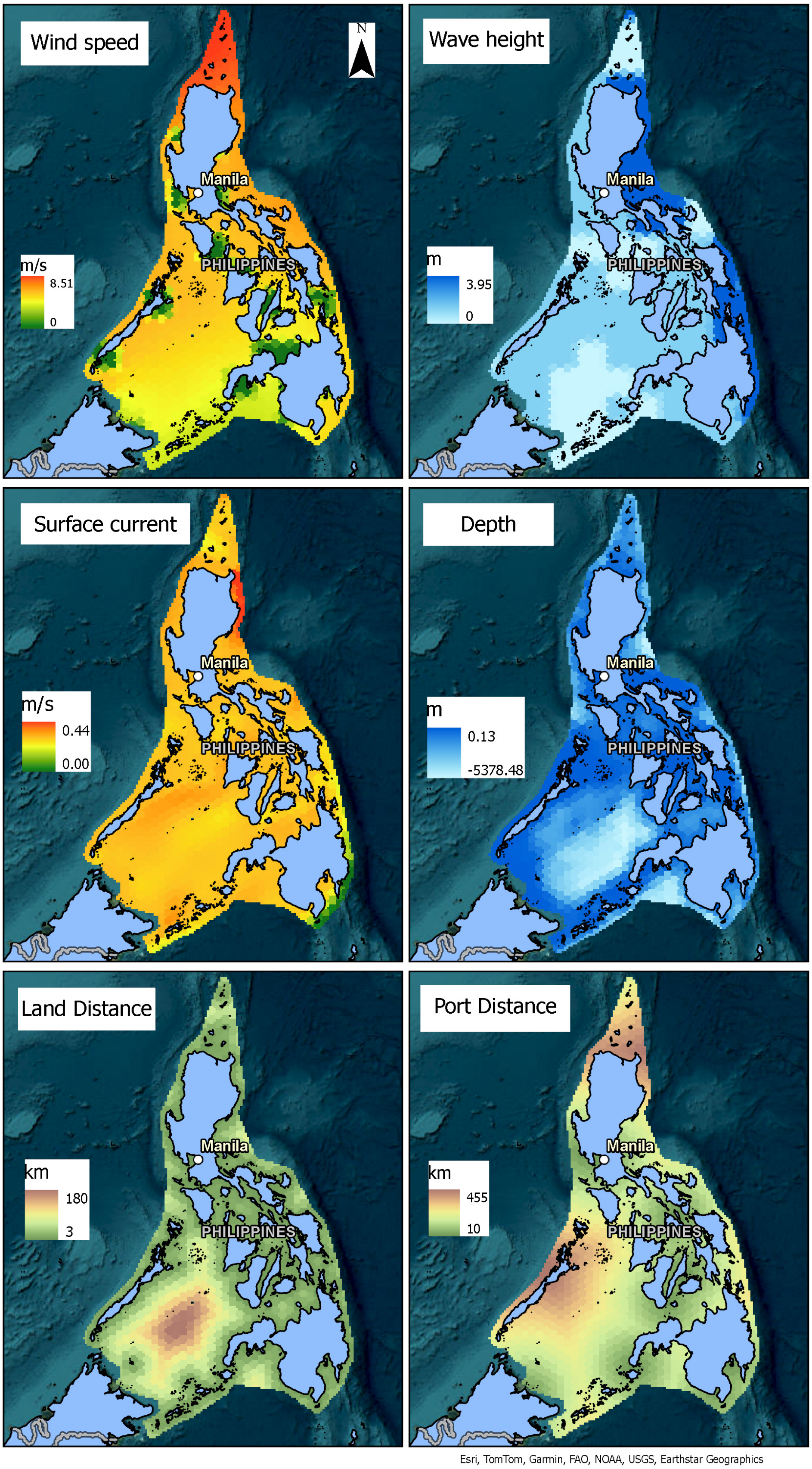


Figure 4. Variables used in Maxent modelling.

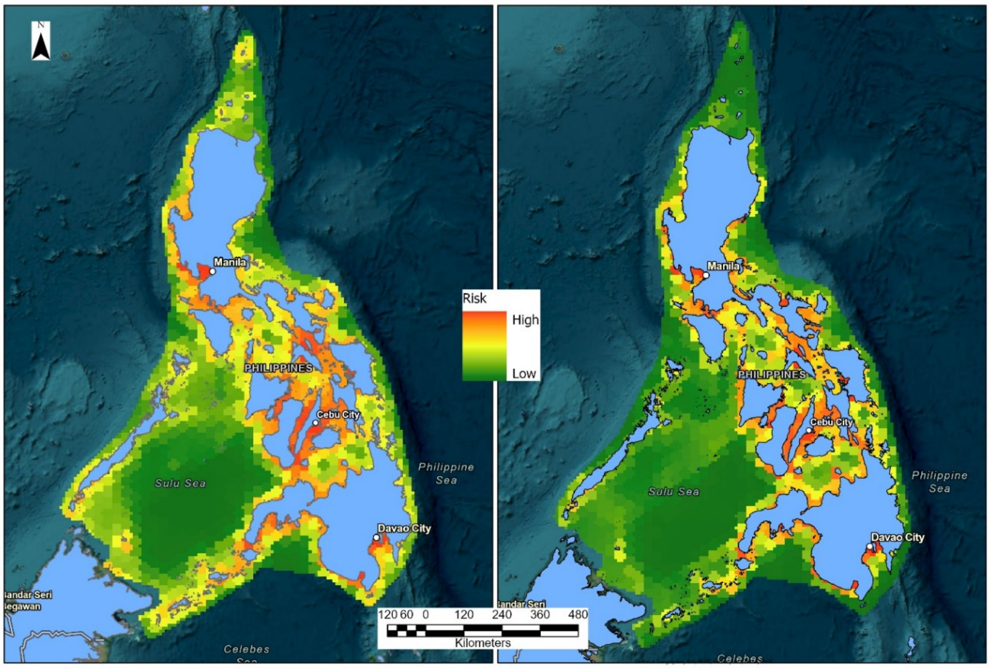


Figure 5. Results of Maxent modelling for PCG (**left**) and GISIS (**right**) data.

In terms of variable contribution to the models, land distance, port distance and depth exhibit the highest gains, thus making the greatest contributions. The effects of environmental conditions on the model are significantly smaller compared to the top contributing variables. Additionally, wave height and wind speed show greater gains for the GISIS dataset compared to surface current, while the values are nearly identical for the PCG dataset (Figure 7).

Results of the model performance show the AUC to be comparable between the two models, with the TSS and Kappa also close to each other (Table 1). Values of the different performance metrics generally show adequate performance of the models in terms of AUC, while the TSS and Kappa are above average.

Table 1. Performance measurements of the Maxent models.

Data	AUC	TSS	Overall Accuracy	Sensitivity	Specificity	Kappa Max
PCG	0.845	0.34128	0.40296	0.95636	0.38491	0.24586
GISIS	0.849	0.30652	0.37310	0.93548	0.37104	0.22094

When the total archipelagic area of suitability maps from Maxent were classified into five distinct categories, ranging from low to high risk, the high-risk areas accounted for 4% of the PCG data and 7% of the GISIS data. While the majority of the total area was considered low to medium-low risk, 4% (PCG) and 7% (GISIS) of the areas within 3 km of the shore belonged to the high-risk category (Table 2).

Table 2. Percentage areas of classified Philippine waters from Maxent output transformed into risk categories.

Category	PCG	GISIS
Low	54%	37%
Medium Low	18%	23%
Medium	13%	17%
Medium High	10%	16%
High	4%	7%

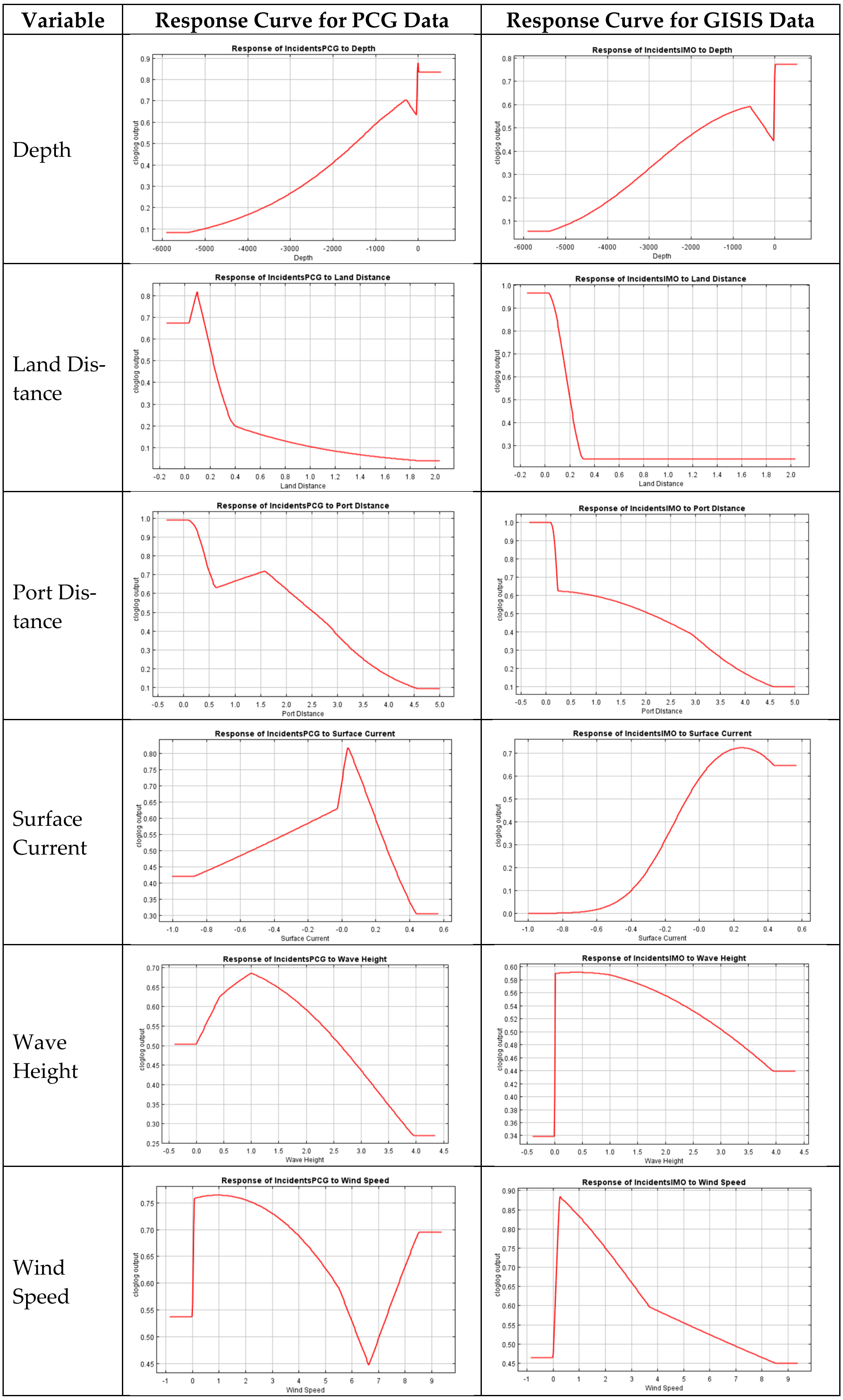
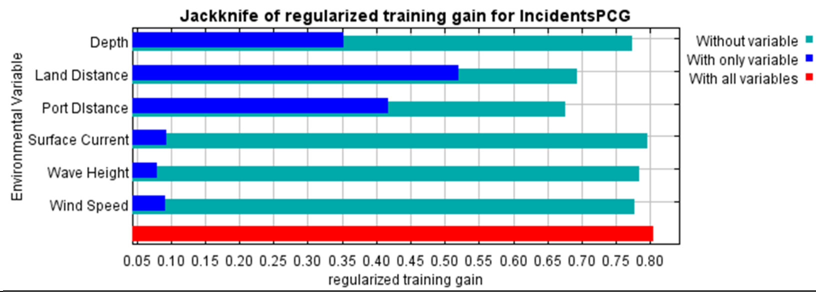


Figure 6. Model response to the variables and the jackknife of test gain for the model.

<table>
<tr><th>Dataset</th><th>Graph of gain</th></tr>
<tr><td>PCG</td><td>
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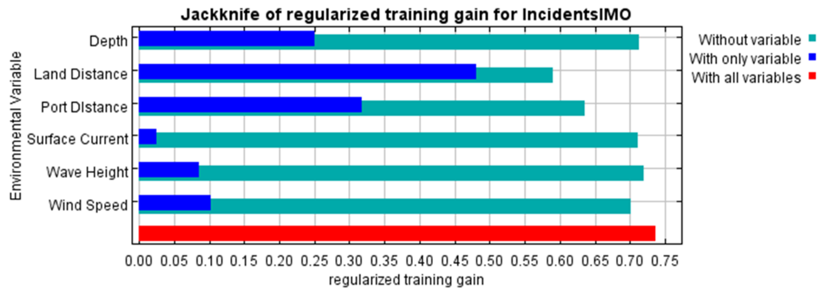
<tr><td>GISIS</td><td>
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Figure 7. Jackknife of variable contributions.

4. Discussion

Results of spatial analysis show a consistent pattern of incidents occurring in areas near land or coastal areas and major ports with shallow depths. The presence of grounding hazards, such as hidden sea-bottom features (shoals, reefs, rocks) or other vessels navigating nearby or close to land, are among the factors that may influence this finding. Such proximity is consistent with global results and studies of individual territories or bodies of water [25,56]. This indicates a need for the nationwide implementation of vessel traffic management systems (VTMS) that provide capabilities for collision avoidance, route planning, monitoring and reporting [22]. Planned implementations in the country include VTMS for major ports such as Batangas, Manila [65], Cebu, Cagayan de Oro and Corregidor [66], reflecting recognition of their necessity. Further study on the development of VMTS, particularly on their influence on the risk map, is needed not only to determine effectiveness but also to provide baseline information for other important areas prone to disasters in the archipelago.

Results of the spatial distribution tools kernel density and hotspot analysis show patterns for both data sets with significant hotspots near busy ports and near land areas. The output of Maxent is slightly different from the first two, mainly due to the use of hexagon centroids or the rarefication of incident locations to eliminate clusters and the influence of environmental variables selected for the study. The high-risk areas identified by Maxent are consistent with the results of kernel density and hotspot tools, with more areas identified by the former as being high risk.

Although the overall percentage of the area of the likelihood component of risk is small, most high-risk areas are near land and major ports with significant shipping and other vessel traffic. Presenting the results of the model as a map showing areas with classified values of the likelihood element of risk provides an informative guide in efforts to institute risk assessment as a valuable tool contributing to safety at sea. Results of the variable contributions emphasise the influence of land distance, port distance and depth, highlighting areas where risk mitigation measures should be prioritised. These may include navigational aids, vessel management systems, updated charts, data for simulation and other available solutions for safety measures. In contrast, surface current, wave height and wind speed have a much smaller impact than the top three contributing variables, indicating that factors related to vessel conditions, such as operations, piloting, management as well as overall shipping conditions are much more influential compared to the environmental conditions used in the model. This result provides a guide for further studies focused on these variables, with the end in view of supporting management decisions on a national scale.

When considering the complexity and multi-stakeholder nature of a maritime risk management effort where government agencies, shipping companies, fishing boat operators, passengers and other organisations are involved, a common information platform that integrates understandable risk maps, repeatable modelling approaches and other forms of knowledge is deemed to be of significant value [67]. Further improvements, including the utilisation or integration with other tools such as the Analytical Hierarchy Process (AHP) and its derivatives, are recommended. Use of AIS data with an appropriate modelling approach is seen to provide more accurate location accuracy and allow the integration of other variables such as heading and speed into the model. The use of real-time position data and big data from AIS, together with machine learning and Artificial Intelligence (AI) approaches [68–70], further provide opportunities for developing effective solutions to improve the management and control systems to enhance the country's maritime safety, as mandated by national policies [71].

5. Conclusions

With the Philippines ranked among the countries with the highest number of maritime accidents, relevant geospatial models offer valuable tools for visualizing and identifying areas of concern. Results show significant hotspots near busy ports and population centres where high volume maritime traffic is expected. Models from geospatial tools in ArcGIS and Maxent provide a quantitative basis for the development of a risk assessment model. High values of risk likelihood provide information on areas where limited resources should be focused to address the high probability of accidents immediately. These maps also underpin information for the development of long-terms strategies and development plans supporting mandates and policies for the enhancement of maritime safety in Philippine archipelagic waters.

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