A Data-Driven Approach to Hurricane Debris Modeling

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Abstract: The large amount of debris generated in the aftermath of hurricane and storm events can cause severe financial and logistical burdens to coastal communities. Existing debris estimation models mainly focus on wind-induced debris and produce estimates with errors of nearly 50%, highlighting the importance of developing more comprehensive models that can account for other types of debris while improving accuracy. Therefore, the objective of this study is to develop a probabilistic framework to estimate the presence and amount of waterborne debris following a severe storm using machine learning (ML) techniques as a function of relevant storm and landcover parameters. Machine learning techniques are leveraged to generate debris presence and volume models, employing pre- and post-event aerial and satellite imagery and a debris removal database for Hurricane Ike, respectively. The results show that the ensemble learning algorithms perform the best for both tasks, with a misclassification error of 5.56% for the debris presence predictive model, and a normalized root mean squared error (RMSE) value of 11.98 for the debris volume model, the lowest RMSE of the tested algorithms. Dual-layer ML models are also investigated, incorporating the debris presence as a predictor in the debris volume model. The results show a percent error of 11.29% for the dual-layer model and an approximately 5.4% increase in performance with respect to the model that does not incorporate debris presence. The generated debris volume and presence models will provide useful tools to inform decision-making, evaluate mitigation strategies, facilitate recovery efforts, and improve resource allocation following a storm event. DOI: 10.1061/JWPED5.WWENG-1945.

Introduction

Debris is one of the most challenging cascading impacts for coastal communities in the aftermath of hurricane events. Communities along the United States coasts frequently experience storm and flood events generating a large amount of debris, and their removal poses an important financial and logistical burden to local, state, and federal governments. For instance, of the $2.2 billion total Public Assistance funds granted to the state and local government agencies following Hurricane Ike (2008), nearly $752 million (34%) were dedicated to debris removal activities (FEMA 2019). The presence of debris around households as well as on roads and bridges not only slows down recovery efforts but can also cause significant disruptions to transportation networks, jeopardizing the accessibility of vulnerable communities to critical facilities such as hospitals or shelters (Balomenos et al. 2019; Kameshwar et al. 2021; Kocatepe et al. 2019; Yin et al. 2017). These debris can cause damage to critical infrastructure systems in case of impacts or damming (Bernier and Padgett 2020; Gonzalez Duenas et al. 2019; Ma et al. 2021; Mauti et al. 2020; Stolle et al. 2020). Moreover, during flood events, hazardous chemical materials commonly stored in households, fuel and oil in flooded automobiles, and construction material such as plywood can become sources of debris and therefore affect public health due to immediate spreading or improper disposal after the storm event (Luther 2006; Reible et al. 2006).

Even though estimates of the total amount of debris produced by natural hazards are useful to allocate resources and to plan required infrastructure such as waste management plants or landfills, information on the distribution of debris over a region is essential for formulating a disaster response (e.g., loss of connectivity on transportation networks), for coordinating disaster cleanup operations (Özdamar et al. 2014), and for planning temporary disaster waste management sites, which are critical for minimizing the costs and duration of cleanup operations (Cheng et al. 2022). Moreover, having information on the geographic location of the debris can also help minimize the exposure of the community to potentially toxic debris. For instance, during Hurricane Katrina, Federal Emergency Management Agency (FEMA) supported the collection of debris from private property in certain regions of Louisiana, Alabama, and Mississippi due to the concerns raised by local governments on the health risk posed to the community by the uncollected debris in these areas (Luther 2006). Some methodologies have been proposed in the literature that are able to capture the spatial distribution of debris over a region. However, these methodologies either focus solely on windborne debris (FEMA 2012; Marchesini et al. 2021; Umpierre and Margoles 2005) and vegetative debris (Escobedo et al. 2009; Karaer et al. 2021; Thompson et al. 2011) or focus on post-storm response using images (Gazzea et al. 2021; Schaefer et al. 2020; Yoo et al. 2017).

Debris mitigation and management strategies are key to the resilience of coastal communities under hurricane hazards, and to support them, it is critical to evaluate the risk of debris accumulation from future storms. Nevertheless, hurricane-induced debris predictive methodologies, independent on their ability to capture the spatial characteristics of the debris, have shown suboptimal predictive performance and focus on specific types of debris. Predictive debris methods such as the ones proposed by FEMA (Hazus) (FEMA 2012) and the United States Army Corps of Engineers (USACE) (Drenan and Treloar 2014), which are commonly used for debris management plans in the United States, consider only

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windborne debris and have shown errors of nearly 50% between estimated and observed debris quantities in past hurricane events (H-GAC 2011; USEPA 2008). For instance, the Hazus method considers debris sources from tree blowdown and damaged buildings but specifies overestimations in the range of 41%–90% for hurricane-induced debris volume (FEMA 2012; Marchesini et al. 2021). Thompson et al. (2011) proposed a statistical model to predict hurricane-induced tree debris in the Houston area leveraging aerial imagery from Hurricane Ike (2008), with overestimations up to 27%. While focusing on vegetative debris, the authors found that the storm predictor variables were not really strong predictors of the debris, corroborating the results of previous studies (Stanturf et al. 2007; Staudhammer et al. 2009; Thompson et al. 2011). However, in these studies, only the wind field characteristics were used to describe the storm. Hurricanes are multihazard events in which the combined action of wind, surge, and waves, interact with the built and natural environment to generate and spread debris. For instance, Hurricane Ike was characterized by large surge and waves, causing widespread damage in the Houston–Galveston region, especially in the area of Bolivar Peninsula where the hurricane made landfall (FEMA 2009). In this area, multiple houses sustained large levels of damage due to the combined effect of surge and wave action, as well as the impact of waterborne debris (FEMA 2009). Therefore, there is a need to propose more accurate predictive methods that can incorporate other types of debris (multihazard action), while considering the spatial characteristics of the debris process.

While most of the hurricane debris predictive models have focused on windborne debris, waterborne debris modeling has been an active area of research in the last decade in the tsunami hazard community. Due to the complexity of the waterborne debris accumulation and motion process, modeling has been mostly focused on experimental work with recent advancements in the incorporation of numerical modeling for tsunami risk assessments. Several laboratory experiments have been conducted to understand waterborne debris impact and damming loads (Mauti et al. 2020; Shekhar et al. 2020; Stolle et al. 2018a, 2020), motion (Nistor et al. 2017; Stolle et al. 2018b), and interactions among debris and between debris and the environment (von Häfen et al. 2021; Park et al. 2021). Recently, efforts to model waterborne debris spreading at a community level have been proposed using advection models (Park and Cox 2019). Nevertheless, not much is known about the genesis and waterborne debris motion under hurricane conditions, and predictive models that consider this specific type of debris are lacking in the literature. Considering this, the potential of historical data from previous hurricane events can be leveraged to forecast waterborne debris accumulation using data-driven modeling. Data-driven models allow discovering patterns in the data and making predictions even when the process or system behind it is not well understood. These models also have the advantage of requiring less computational effort and allow an efficient evaluation of different scenarios, facilitating informed decision-making.

Therefore, the objective of this study is to develop a data-driven framework to predict the amount of waterborne debris following a severe storm using machine learning techniques. Models to predict waterborne debris presence and volume are developed as a function of relevant predictors of the physical process while accounting for its spatial characteristics. As a proof of concept, the proposed approach is applied to the Houston–Galveston region using data from Hurricane Ike, which made landfall in 2008 and was predominantly characterized as a surge-wave event. First, a data processing workflow to obtain the necessary predictors and response variables for the model is introduced. Then, a computational framework to test the performance of a dual-layer model is presented along with the individual predictive debris presence and volume models. Several machine learning techniques are applied and compared to select the debris presence and volume predictive models with the best performance. This paper ends with a discussion of the results and general conclusions.

Data-Driven Framework for Waterborne Debris Modeling

The debris generated in the aftermath of natural hazards can affect communities in various aspects, from disruptions of transportation networks due to the presence of debris to challenges with disposal due to saturation of landfills. Acknowledging this, two different waterborne debris models are proposed, one to predict debris presence and one for estimating debris volume over a region. The waterborne debris presence predictive model allows one to predict the existence of debris in a specified area in the aftermath of the storm event in regions that experienced flooding. Similarly, the waterborne debris volume model estimates the total amount of debris (in m^3) expected in a delimited area in the aftermath of the storm in regions that experienced flooding. With the aim of enhancing the model predictive capability, the nesting of the two models is also explored by investigating the effect that observations regarding debris presence have on the performance of the debris volume model. This is important, since incorporating information on the existence of debris in a particular area can help inform the debris volume model of important characteristics of that area that favor debris accumulation. To address these points, a computational framework, shown in Fig. 1, is proposed to develop the two waterborne debris predictive models (presence and volume) and to analyze the effect of including debris presence as a predictor in the debris volume model.

To formulate a predictive model, two basic components are needed, the predictors and the response. The former refers to the input parameters of the model, which need to be chosen as variables that might have an influence on the phenomenon under study. The response is the predicted variable, in this case, the debris presence and the debris volume, and that constitutes the output of the model. The combined predictors and the response variable form a data set in which the different machine learning algorithms are tested. The data set is divided into three groups, namely, a training and validation data set, a test data set, and a blind test data set. The training and validation data set is used to train the machine learning model and further perform hyperparameter tuning. The test set is a data set never seen by the model during the training phase and is used to select the model class having the best performance. A blind test set is also included in this study to evaluate the performance of the proposed dual-layer framework. Because the data have associated spatial characteristics, a geographic information

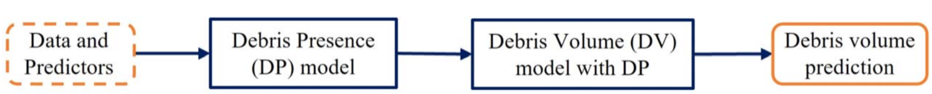

Fig. 1. Proposed computational framework. The dashed line represents the data needed as inputs for the models and the solid line denotes the data outputs of the predictive model.

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system (GIS) software (version ArcMap 10.5.1) is needed to map the data, analyze it, visualize it, and couple the different data sets. The methodology to process the different data sets and formulate the waterborne debris predictive models is detailed subsequently and summarized in Fig. 2.

Data Processing Workflow

Identification of the Surge Zone

First, the potential area affected by waterborne debris is delimited using the surge zone of the hurricane. For the case study, the surge zone is obtained from ADCIRC + SWAN computer simulations for Hurricane Ike (CGH 2017). Hurricane Ike made landfall in the Houston–Galveston region in 2008 and generated large storm surge and waves in the area, with the highest surge levels reaching 5 m (Sebastian et al. 2014). The hindcast model for Hurricane Ike was validated against measured high water marks along the Gulf Coast (Hope et al. 2013; Sebastian et al. 2014). The storm simulation provides hourly estimates of different surge, wave, and wind intensity parameters for 4 days (96 h), which are extracted for the Houston–Galveston region and used to define the surge zone and relevant storm intensity parameters. In the second step, the surge

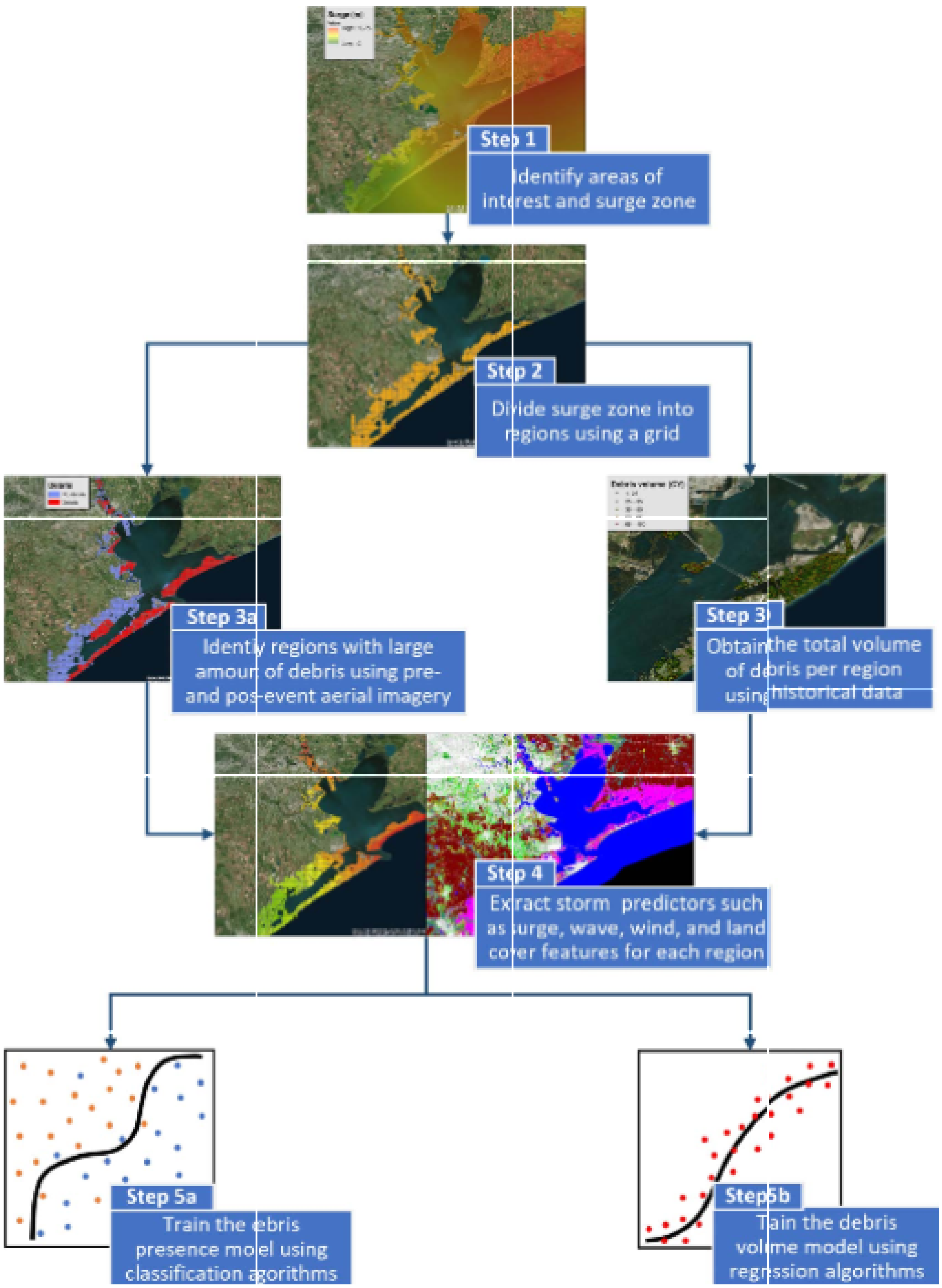

Fig. 2. Methodology to formulate a waterborne debris dual-layer model. (Sources: Esri, DigitalGlobe, GeoEye, i-cubed, USDA FSA, USGS, AEX, Getmapping, Aerogrid, IGN, IGP, swisstopo, and the GIS User Community.)

zone is further divided into regions for geospatial analysis purposes. This is done by creating a grid in GIS software. In this study, a grid cell size of 0.5 km by 0.5 km is employed. The grid size is determined by performing a sensitivity analysis with squared grid cell sizes of 1, 0.5, and 0.25 km; a 0.5 km grid cell size offers the best performance in terms of predictive capability.

Waterborne Debris Presence and Volume Databases

The third step consists of obtaining and preprocessing the debris presence and volume databases. A data processing workflow is developed leveraging aerial imagery and historical data from Hurricane Ike to form the response data. For the debris presence data, pre- and post-event aerial and satellite imagery (NOAA 2008; USGS 2017; USACE 2017) are used to manually identify cells in the 0.5 km grid with debris accumulation in the aftermath of Hurricane Ike. Leveraging the pre- and post-imagery, polygons are manually drawn around regions with debris accumulation. The polygons are then overlayed with the $0.5\ \text{km} \times 0.5\ \text{km}$ grid. A cell fully enclosed in the polygon or in which 25% of its area is enclosed in the polygon is considered as having a debris accumulation. In the future, image segmentation algorithms can be explored to automate the process of debris identification from images. However, this is out of the scope of the present study. Using GIS software, if debris is identified in the region, the respective grid cell is marked with 1 or 0 otherwise.

For the debris volume model, a database consisting of more than 200,000 locations in the Houston–Galveston region, with information such as debris removal quantities and location for Hurricane Ike, is used in this study as input for the model. This database relies on the FEMA Public Assistance Project Worksheets (FEMA 2017). To receive FEMA assistance, local governments must provide details of their debris removal projects such as debris quantities, type of debris, the location where debris is removed, among others. The worksheets for Hurricane Ike were provided by the Houston–Galveston Area Council (H–GAC) and the consulting and engineering firm Tetra Tech (H–GAC 2022; Tetra Tech 2022). Therefore, the debris removal database for Hurricane Ike provides information on the addresses where the debris was picked up. However, geographical coordinates are needed to process the data in a GIS analysis software. Therefore, an automated workflow in DesignSafe-CI (Rathje et al. 2017) is leveraged to preprocess, analyze, and visualize the data. Python scripts are developed to geocode each debris point using web scraping techniques through Google application programming interfaces (APIs). These codes are then used to develop Jupyter Notebooks to connect directly with the GIS software for visualization and geographic analyses purposes (Dukes 2019; Molina et al. 2019). The total debris volume per region is then obtained as the sum of the volume of all the points lying in each grid cell of the surge zone. Given the large uncertainty in the debris accumulation and spreading process, as well as the need for a sufficient amount of data to leverage surrogate modeling techniques, debris points within a radius of 0.25 km outside the surge zone boundary are assigned to the closest grid point. This boundary represents an approximated perimeter of the Hurricane Ike surge zone based on the hindcast storm simulations.

Model Predictors

In the fourth step, predictors with a potential influence on the waterborne debris process are obtained. On previous studies and observations during past hurricane events (Karaer et al. 2021; Thompson et al. 2011), the storm and land cover parameters have shown significance in predicting debris in the aftermath of the event. The loads imposed during hurricane events on the built and natural environment can make vulnerable components such as houses and trees potential sources of debris. Therefore, it is expected that the storm intensity parameters will influence the debris accumulation process. Likewise, potential sources and types of debris can be identified in a region based on urban development patterns, and the coastal landscape is also expected to have an influence on the debris-spreading process.

Eleven storm predictors for storm surge and wind characteristics are obtained from the ADCIRC + SWAN hindcast simulation of Hurricane Ike and RMS HWind data (Powell et al. 1998): (1) surge depth, (2) surge velocity in the x- and (3) y-directions, (4) bathymetry, (5) wave height, (6) wave period, (7) wave direction, (8) wind velocity, (9) wind steadiness, (10) wind duration, and (11) wind direction. In order to couple the storm predictors with the debris presence and volume response variables, the mean value of each one of the storm parameters per grid cell is obtained. In future studies, second-order predictors such as momentum flux and wave force will be tested.

The 2008 land cover features are obtained from the National Land Cover Data Set (MRLC 2008). Given that in each region more than one type of land cover might be present, the ratio of each land cover type per grid cell is obtained. For our case study, nine land cover features are identified in the area: (1) open water, (2) emergent herbaceous wetlands, (3) grassland/herbaceous, (4) woody wetlands, (5) pasture/hay, (6) developed open space, (7) developed low intensity, (8) developed medium intensity, and (9) developed high intensity The final data set consists of 20 predictors (11 storm variables and 9 land cover features corresponding to the ratio of each land cover type identified in the area) and 2 response variables, debris presence (1 or 0) and debris volume (in cubic meters), per grid cell.

Final Data Set

The final data set consists of 1,074 observations (i.e., 1,074 grid cells) of debris presence (binary-value) and debris volume (real-value) in cubic meters along with the 20 predictors. From these observations, 174 observations are randomly selected as the blind test set and the remaining 900 observations are further utilized as training, validation, and test sets. The 900 observations are randomly split into 80% training and validation data set and 20% test data set. The training and validation data set is used to perform hyperparameter tuning of various machine learning models adopting 10-fold cross-validation, whereas the test set is used to select the best predictive model for debris presence and debris volume. The blind test data set is used to evaluate the performance of the proposed dual-layer framework in the debris volume predictive task (Fig. 1). The blind test data set was separated initially from the data to avoid any potential bias originating from the training and validation phase of the models. Fig. 3 shows the division of the original data set as explained previously.

Predictive Models for Debris Presence and Debris Volume

Debris Presence Predictive Model

The objective of this section is to formulate a predictive model that can provide estimates of the total volume of debris at a particular region leveraging debris presence data, multihazard storm intensity parameters, and land-cover features. First, a machine learning model that can predict the presence or the absence of debris is developed. Such a task can be achieved by adopting a binary classification model whose response is a binary label (1 or 0) having a 20-dimensional input (predictors). Several classes of machine learning models are adopted and compared to select the model with the highest accuracy in predicting the class label.

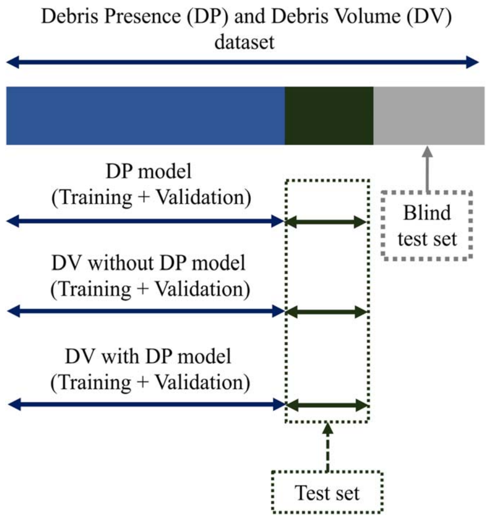

Fig. 3. Division of a debris data set.

Table 2. Misclassification error for the debris presence model

No.	Methods	Misclassification error
1	Logistic regression	0.2667
2	Logistic regression with LASSO	0.3056
3	Support vector machines	0.1167
4	Ensemble learning	0.0556[a]
5	Artificial neural network	0.1000

[a]Classification model with the highest accuracy.

The models tested include logistic regression (Hosmer et al. 2013), logistic regression with LASSO (Wu et al. 2009), support vector machines (SVMs) (Gunn 1998), ensemble learning (Sagi and Rokach 2018), and artificial neural network (ANN) (Jain et al. 1996). The hyperparameters of the individual machine learning models are tuned by performing 10-fold cross-validation using the training and validation data set. The different hyperparameters for each one of the classification models are listed in Table 1. The Statistics and Machine Learning Toolbox (MathWorks 2021) within MATLAB (version R2018a) is used to perform the training and tuning of the machine learning models. Once the tuning parameters are optimized, the performance of the trained models is compared by evaluating the misclassification error on the test data set. Table 2 compares the misclassification errors of the different trained machine learning models. From this table, the trained ensemble learning model displays the best performance for predicting the presence or absence of debris. The tuned hyperparameters of the ensemble learning model with the weak learners as decision trees are (1) method: AdaBoost, (2) number of learning cycles: 471, (3) learning rate: 0.18179, (4) minimum leaf size: 7, (5) maximum number of splits: 684, and (6) split criterion: deviance.

The high accuracy (94.44%) of the ensemble learning algorithm in predicting debris presence highlights the ability of machine learning algorithms to capture debris behavior in the aftermath of storm events. This means that the model can provide high confidence estimates on the areas that debris will be located in the aftermath of storm events, facilitating disaster response efforts, planning of debris removal activities, transportation and accessibility analysis, as well as allocation of resources. For instance, if the potential spreading of debris is known before a hurricane makes landfall, stakeholders can plan for rapid debris removal from critical roads to ensure accessibility of the community to critical facilities and allow first responders to reach high-risk facilities such as oil refineries (e.g., fires can be triggered in oil refineries in the aftermath of hurricane events).

Further insights can be gained when analyzing which variables are more significant for predicting debris presence in a region. Fig. 4 shows the relative importance of each one of the predictors in the debris classification model. Overall, the storm variables have a higher significance relative to the land-cover predictive variables. The predictors associated with the wind field show the highest importance, with the wind steadiness showing the maximum relative importance, followed by the wind direction, wind speed, and wind duration. Nevertheless, the surge depth, wave height, and wave direction also appear as important predictive variables in the model. This emphasizes the need to consider the multihazard characteristics of hurricane and storm events when analyzing debris behavior in coastal regions. The land-cover features, even when showing the least relative importance, can also offer key insights into the debris accumulation and spreading process. For example, within the land-cover variables, the ones associated with development characteristics stand as important predictors. Developed land-cover areas are characterized by some presence of constructed materials (e.g., housing units) and a considerable percentage of impervious surface. This suggests a relationship with the debris process and the built environment and can help inform future urban planning strategies in coastal areas.

Debris Volume Predictive Model

Several regression models are evaluated and compared in order to formulate a predictive model for waterborne debris volume. Two

Table 1. Machine learning classification and regression algorithms and their respective hyperparameters tested for the debris presence and volume models

Model	Hyperparameters
Logistic regression	Regularization parameter.
Logistic regression with LASSO	Sparse regularization parameter.
Support vector machines	Real-valued box constraint, kernel function (linear, Gaussian, or polynomial), kernel scale in case of Gaussian kernel, and polynomial order (2, 3, or 4) in case of the polynomial kernel.
Ensemble learning	Methods of bagging (random forest) or boosting, number of learning cycles, minimum leaf size, and maximum number of splits. For the boosting method, further hyperparameters include the learning rate and the choice of the boosting algorithm (adaptive boosting, gentle adaptive boosting, adaptive logistic regression, linear programming boosting, robust boosting, and random under sampling boosting). The weak learners are chosen as decision trees.
Neural network	Number of neurons in the hidden layer, activation function (sigmoid, hyperbolic tangent, or rectified linear unit), and regularization parameter.
Ridge regression	Regularization parameter.
Lasso regression	Regularization parameter.
Elastic net	Regularization parameter.

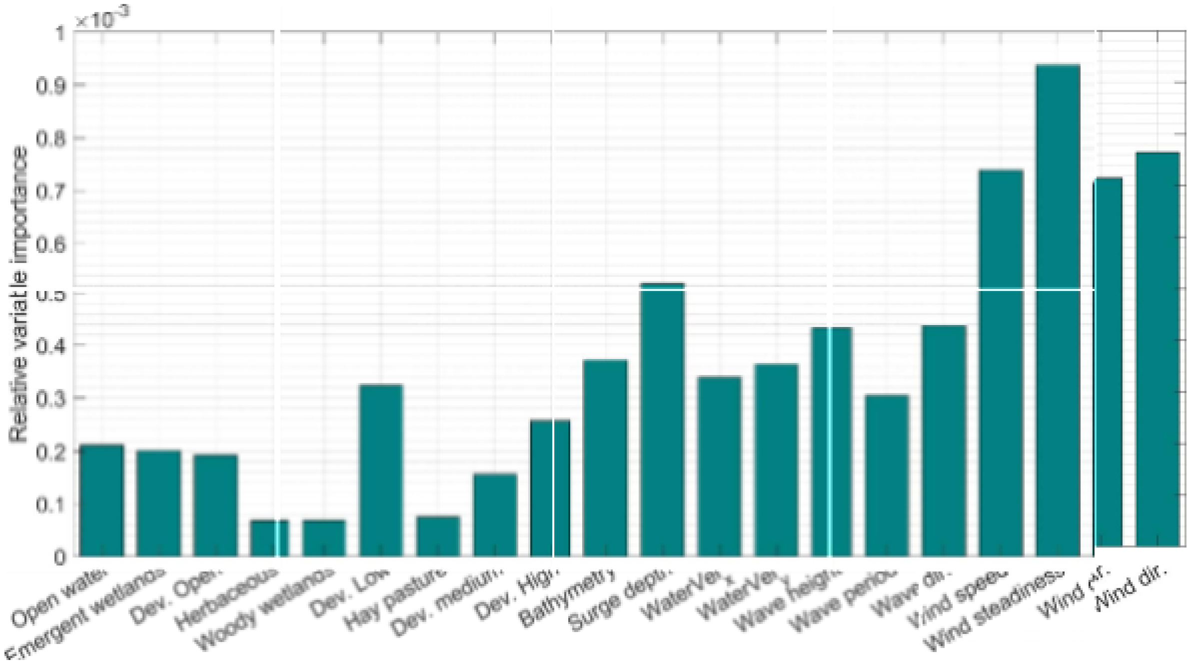

Fig. 4. Relative importance of predictors in a debris classification model.

machine learning models using the training and validation data set are proposed; one model estimates the debris volume without the debris presence data (20 predictors), and the other model estimates the debris volume with the debris presence data, leveraging the debris presence data as one of the predictors (21 predictors). Ridge regression (Friedman et al. 2001), LASSO (Friedman et al. 2001), elastic net (Friedman et al. 2001), SVM regression (Gunn 1998), ensemble learning (Sagi and Rokach 2018), and ANN (Jain et al. 1996) are trained using the training and validation data set. The hyperparameters of each one of the models are listed in Table 1.

The normalized root mean squared error (RMSE), obtained on the data belonging to the test set, is used to compare the goodness of fit of the individual regression models. The normalized RMSE is a dimensionless metric that estimates the standard deviation of the residuals (i.e., difference between the predicted values and the observed ones). Lower values (toward zero) of RMSE indicate a better model performance. Table 3 compares the performance of the trained machine learning models (on the test data set) for the tasks of predicting the debris volume with and without the debris presence data. The ensemble learning regression model with decision trees as weak learners performs the best for both tasks, having the lowest normalized RMSE value of the regression models. Table 4 lists the tuned hyperparameters of the ensemble learning models, both considering and not considering the debris presence data. The predictive model for debris volume that leverages debris presence as one of its predictors performs better than the one without debris presence information. Debris accumulation and spreading is a complex process, in which the factors of the natural and built environment interact with each other in space and time. Having information on debris presence in the aftermath of a storm, for example, can provide insights into regions that, due to topographical characteristics or presence of barriers, promote debris accumulation. For instance, if a region presents a large number of dunes or man-made barriers such as fences, it is more likely that debris will accumulate on their perimeter. Moreover, given that the debris is transported by the water, low-lying areas will be more prone to debris settlement. The debris presence data help to capture these characteristics of the debris process, informing the debris volume model of places that are more likely to present debris accumulation. This is of great importance in modeling complex processes in which the physics of the problem have not yet been well understood (like the waterborne debris process) in helping to identify important characteristics of the process in an indirect manner. In this application, for example, the binary classification helps give more weight to regions where debris has been observed, thereby improving the performance of the debris volume model. Future studies can explore these interactions of debris settlement with topographic, natural, and constructed barriers or shields.

Fig. 5 shows the relative variable importance for the best performing regression model (i.e., ensemble learning model leveraging debris presence data) in the debris volume predictive task. In

Table 3. Debris volume model performance in terms of normalized RMSE

No.	Methods	Normalized RMSE	
		Without DP	With DP
1	Ridge	14.3126	14.2689
2	LASSO	14.4376	14.3870
3	Elastic net	14.3081	14.2732
4	Support vector machines	14.6940	14.6082
5	Ensemble learning	12.6985	11.9807[a]
6	Artificial neural network	14.0019	14.1293

[a]Regression model with the best performance.

Table 4. Best hyperparameters of the ensemble learning models for the debris volume predictive task

Hyperparameter	Without DP	With DP
Method	LS boost	LS boost
Number of learning cycles	156	499
Learning rate	0.0905	0.00778
Minimum leaf size	4	3
Maximum number of splits	542	657
Number of variables to sample	2	1

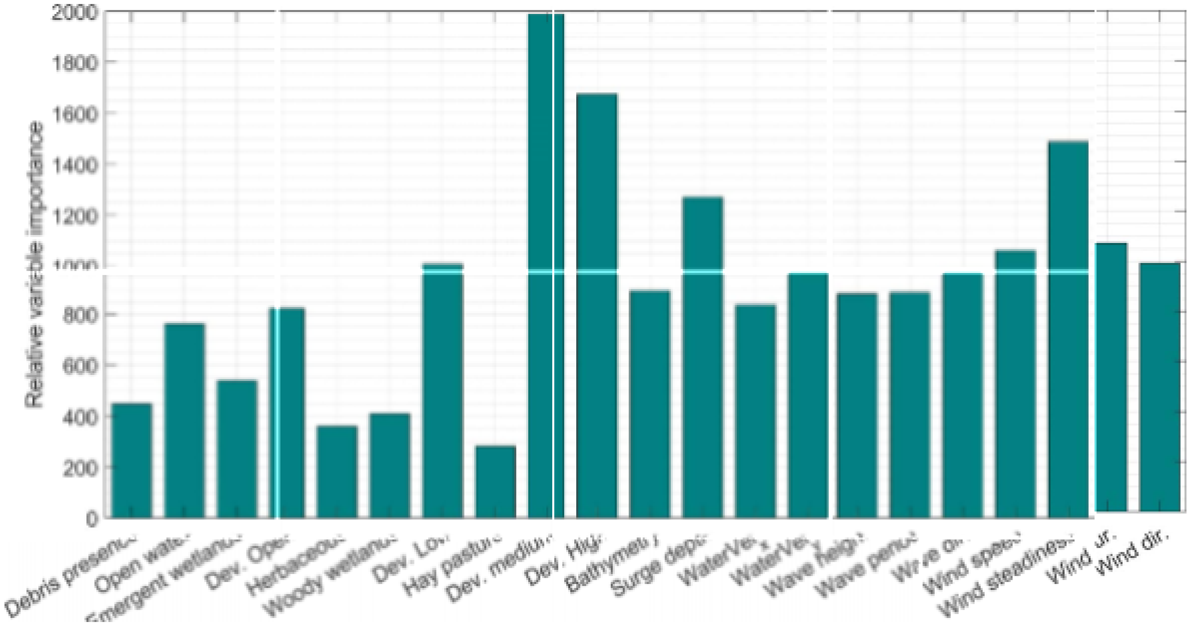

Fig. 5. Relative importance of predictors in a debris volume regression model.

general, the storm predictive variables show a more consistent relative importance in the model than the land cover features. However, the two highest ranked variables in the regression model are land cover features, developed medium and developed high. These variables are followed by the wind steadiness and the surge depth in relative importance. When examining the storm variables, predictive variables such as the water velocity and wave direction have a relative importance similar to the wind field predictive variables (i.e., wind speed, duration, and direction). This reiterates the need for incorporating the surge and wave characteristics when analyzing the debris spreading and accumulation process. From the land cover predictive variables, the ones associated with development show the best relative importance. Therefore, areas with varying levels of urban development and imperviousness will have an effect on the amounts of hurricane-induced debris, as observed in the debris presence predictive model. It is noteworthy that the debris presence does not show a preeminent significance in the debris volume model. Nevertheless, and as mentioned previously, including the debris presence data improves the predictive capability of the model (improvement of 5.7% with respect to the best predictive model that does not include the debris presence data).

It is important to mention that the predictive debris presence and volume models were trained with the data collected in the aftermath of a single hurricane event (Hurricane Ike in 2008). It is expected that with a more robust data set that incorporates debris presence and volume data from different storms and hurricane events, the model performance will be improved. Therefore, platforms to share debris data should be promoted to enhance the prediction capabilities of waterborne debris models (Rathje et al. 2017; Wartman et al. 2020).

Performance of the Proposed Framework: A Dual-Layer Model

The effectiveness of the framework (a dual-layer model) to predict waterborne debris volume is assessed by comparing its performance with two alternative model approaches: only using the trained debris volume model without including debris presence as a predictor and using actual debris presence data as a predictor in the debris volume model. Fig. 6 shows a scheme to compare the predictive capabilities of the three model approaches. The blind test data set, which is not part of either the training, hyperparameter tuning, or model class selection step, is used to perform an unbiased evaluation of the models. The final predictive ensemble learning–based classification and regression models are trained using the combined training and validation and test data set, with the selected values of the corresponding hyperparameter presented in the previous section. The overfitting of the trained model is averted by keeping the values of hyperparameters in this training step the same as the ones obtained through 10-fold cross-validation in the previous step.

As mentioned previously, 174 data points are kept aside as the blind test data set from the original data. The percent error is used to estimate the performance of each one of the model approaches, by comparing the actual debris volume with the predicted debris volume corresponding to the blind test data set. As seen in Table 5, the dual-layer model shows the best performance with an error percentage of 11.29. This percentage is significantly lower than that of the existing models in the literature for hurricane-induced debris, highlighting the potential of dual-layer machine learning models and the incorporation of multihazard storm parameters for predicting complex phenomena such as estimating the final location and amount of debris following storm events. Moreover, to provide insights regarding the robustness of the trained machine learning algorithms adopted in each of the three model approaches, 1,000 instances of bootstrap samples (Efron and Tibshirani 1994) are generated from the 174 blind test data points. Each of the bootstrap samples (having 174 data points) is generated by adopting random sampling with replacement from the original blind test data set. Subsequently, the normalized RMSE is evaluated for each of the 1,000 samples per model approach.

The mean and the coefficient of variation (COV) of the evaluated normalized RMSE are reported in Table 5 for the three model approaches. The model approaches that take into account the presence of debris either using the available data or using the trained debris presence model perform better than the one that does not consider the presence of debris as a predictor. For

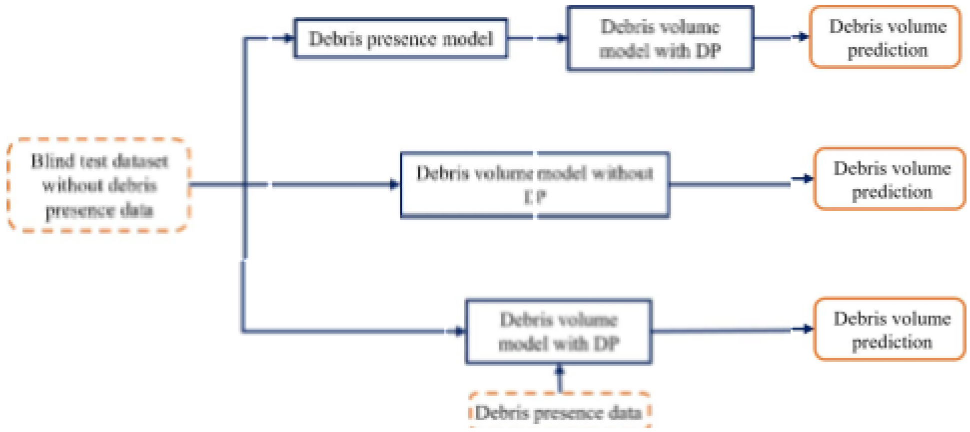

Fig. 6. Proposed scheme to compare dual-layer model performance.

Table 5. Comparative performance of the proposed framework in terms of normalized RMSE and the percentage of error with respect to the collected debris data

Modeling approach	Normalized RMSE Mean	COV	% Error
Debris volume model combined with the debris presence model (dual-layer model)	11.3216[a]	0.1505	11.2910[a]
Debris volume model using debris presence data	11.3712	0.1484	13.2292
Debris volume model without debris presence	11.9737	0.1029	18.2311

[a]Modeling approach with the best performance.

instance, the dual-layer debris volume model shows an improvement rate of approximately 5.4% over the debris volume model that does not include debris presence information. Moreover, the difference in performance between the model that considers the debris presence data and the dual-layer model (combination of the debris presence and debris volume model) is marginal, indicating that the adoption of the predictive debris presence model does not hinder the performance of the framework. A histogram plot of the normalized RMSE evaluated using the 1,000 bootstrap instances is shown in Fig. 7, along with the fitted probability density function for a normal distribution having parameters, as reported in Table 5. The low coefficients of variation corroborate the robustness of the proposed data-driven framework to predict the amount of waterborne debris.

As an illustration of the applicability of the proposed framework, the dual-layer predictive model is leveraged to forecast the expected amount of debris for Galveston Island, TX, if impacted by a storm with an approximate 500-year return period and assuming 2020 land cover conditions. Storm FEMA36 is a probabilistic storm developed as part of the Flood Insurance Study (FEMA 2013) that approximately provides still water elevations of a 500-year return storm event in the Houston–Galveston region (Ebersole et al. 2015). The ADCIRC + SWAN

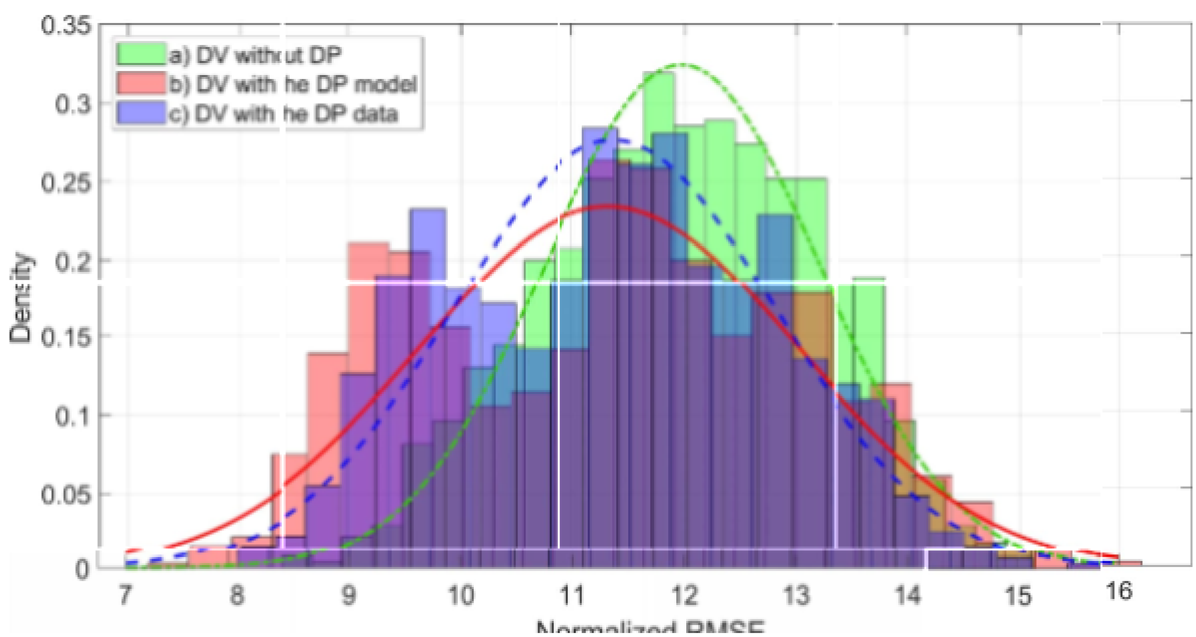

Fig. 7. Histograms of the normalized RMSE evaluated using 1,000 bootstrap samples: (a) debris volume (DV) predictive model without using debris presence (DP) as a predictor; (b) debris volume predictive model combined with the debris presence predictive model (dual-layer model); and (c) debris volume predictive model using debris presence data.

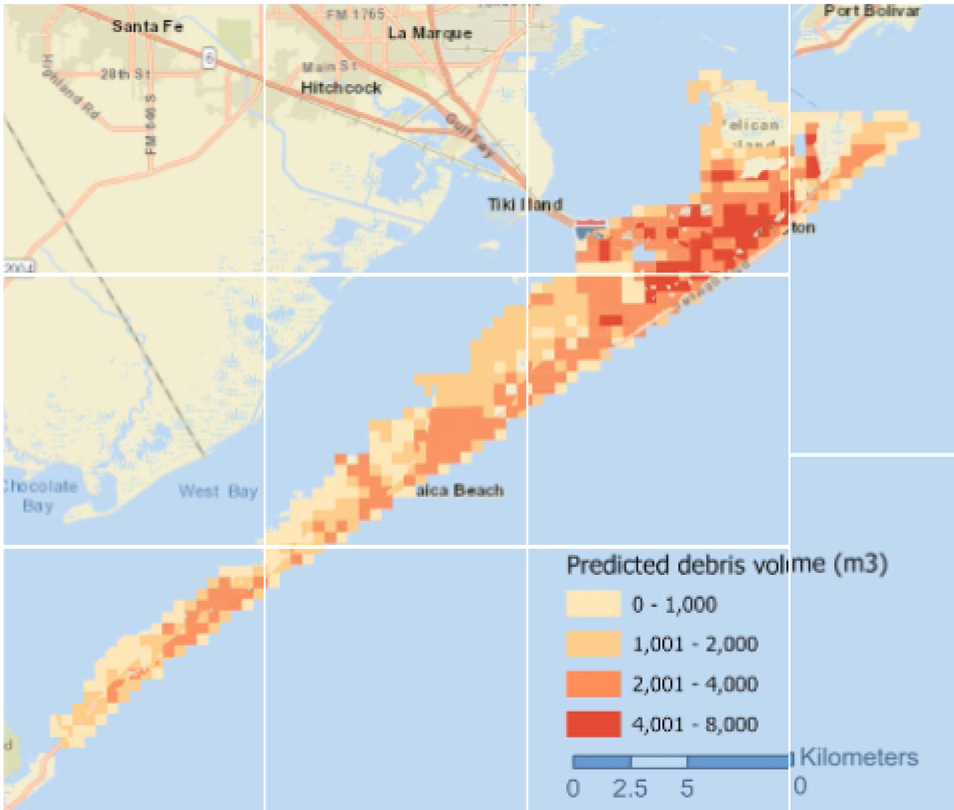

Fig. 8. Application of the proposed framework to Galveston Island, TX, under FEMA36 storm conditions and 2020 land cover parameters. [Sources: Esri, DeLorme, HERE, USGS, Intermap, iPC, NRCAN, Esri Japan, METI, Esri China (Hong Kong), Esri (Thailand), MapmyIndia, TomTom.]

simulation of the FEMA36 (SSPEED Center 2022) storm is used to inform 8 of the 11 storm predictors: the surge depth, surge velocity in the x- and y-directions, the bathymetry, wave height, wave period, wave direction, and wind velocity. To estimate the wind steadiness at each point, the methodology proposed by Berkovic (2018) is leveraged to compute the wind steadiness parameter using the hourly wind velocities of the storm. The wind duration is computed based on the duration of high winds over a wind velocity threshold at each point using the wind field output of the storm simulation. Details on the computation of the high wind velocity threshold and its duration can be found in Kopp et al. (2021). Lastly, the wind direction is obtained as the angle between the two wind velocity components. Moreover, the nine land cover predictors are informed by the 2020 land cover parameters of the area (MRLC 2020). Fig. 8 presents the forecasted debris volume and distribution over Galveston Island, TX, leveraging the dual-layer predictive model. It can be seen that the largest amounts of debris are on the urban core of the island, and that in the South-West region of the island, much of the accumulation is concentrated along the coast. It is important to notice that the forecasted debris accumulation correlates well with the building distribution in the region. As mentioned in the previous section, the land cover features associated with development are important variables for predicting both debris presence and debris volume. More specifically, in the debris volume model, the developed medium and developed high land cover features present the highest relative variable importance. These two land cover features are characterized by the presence of constructed materials such as single-family housing (more predominant for developed medium) and apartment complexes or industrial/commercial areas (developed high) (MRLC n.d.). Thus, it is expected that highly constructed areas will have larger levels or debris volume. This showcases the ability of the model to spatially characterize the debris distribution and accumulation over a region, which is of extreme importance for developing debris management plans and effective mitigation strategies in the aftermath of storm events. Machine learning models also have the advantage of being fast and easy to use, which can be of benefit to local governments and stakeholders, not only on the planning side but also for initiating immediate response after a storm.

Conclusions

This study explores the capabilities of data-driven models to forecast waterborne debris presence and volume over a region in the aftermath of storm events. A computational framework is proposed to estimate the presence and volume of waterborne debris and explore the effectiveness of using dual-layer models, incorporating the debris presence as a predictor of the debris volume predictive model. The framework is applied to the Houston–Galveston region by leveraging data from the 2008 Hurricane Ike, which was characterized by large surges and wave loads. A methodology is also proposed to process spatially distributed waterborne debris data to inform the predictive models. The presence or absence of debris is assessed using pre- and post-aerial images of the event. For each region (i.e., grid cell), a binary label is assigned, with 1 representing the presence of debris and 0 its absence. Further, an automated data processing framework is leveraged to geocode a debris removal database collected in the aftermath of Hurricane Ike. The framework is coupled with GIS to preserve the spatial characteristics of the data. To approximately capture some of the physics of the debris process, land cover and multihazard storm intensity parameters are chosen as predictors of the model, given their relevance in the composition and accumulation of hurricane-induced debris and observations during past storm events.

Leveraging these data sets, different machine learning classification and regression models are evaluated and compared to find the ones with the best performance to predict the presence and volume of waterborne debris. The results show that the ensemble learning models have the best goodness of fit for both the classification of debris presence or absence and for the regression task of predicting debris volume. Moreover, two different modeling approaches of computing waterborne debris volume are compared, with the debris volume predictive model that incorporates evidence on debris presence showing the best performance. The robustness of the methods is also investigated by creating 1,000 bootstrap samples. The results show that the model that incorporates debris data as a predictor performs the best with a normalized RMSE of 11.32 and a percent error of 11.29%. These results are considered satisfactory when compared with existing hurricane-induced debris models in the literature, which can lead to errors up to 50%. Moreover, an analysis of the relative importance of the predictive variables in the models highlights the relevance of considering surge- and wave-related intensity parameters in the debris accumulation process, which existing models fail to address. The land cover features related to development also show significance in both the debris presence and debris volume predictive models, hinting at important correlations of building performance and the debris accumulation process.

While the results of this study show the feasibility of data-driven models to predict waterborne debris presence and volume, future studies should aim to address data constraints and quality, automate processing tasks such as debris presence labeling, perform sensitivity analyses, and expand the set of predictors. Moreover, in the future, the debris transport analysis and the relationship between debris generation and accumulation can be pursued using the forcing from the ADCIRC + SWAN model and relevant characteristics of the built and natural environment. Future studies can also explore the cascading consequences of debris, including subsequent damage to structures or functionality impairment of distributed infrastructure. Moreover, given that changes in the climate are making flood and storm surge events more frequent, it is important to establish effective methodologies to analyze the potential risks for coastal communities under this cascading effect. Therefore, experimental and numerical work on the waterborne debris process for hurricane hazard and varying conditions is also needed, as well as a more comprehensive set of predictors that can explain this complex process. In this regard, ongoing research is exploring feature engineering techniques informed by engineering knowledge that can increase our understanding of the debris process, help identify important variables, and provide probabilistic estimates of debris accumulation over a region.

Data Availability Statement

Some data used during the study were provided by a third party (wind field intensity parameters and the debris removal database). Direct requests for these materials may be made to the provider as indicated in the Acknowledgements. All the other data (debris presence database, storm intensity parameters, and land cover model predictors), models, and codes that support the findings of this study are available from the corresponding author upon reasonable request.

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