A Bayesian marine debris detector using existing hydrographic data products

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***Abstract*—A detection methodology for marine debris presence after a natural disaster is described. The methodology is based both on a predictive model and a Bayesian hierarchical spatial method. The chosen fusion approach relies on auto-logistic regression to weight the outputs of multiple target detection algorithms, as well as to capture the intrinsic processes related to the presence of marine debris. The algorithms are applied to existing hydrographic data products (e.g., bathymetric surfaces, backscatter mosaics). The approach, in active development, is demonstrated and tested both with artificial and real survey data. The scalability of the technique permits its straightforward extension to additional detection algorithms for *ad-hoc* data products.**

Keywords—Bayesian inference; MCMC; hierarchical model; DTM; acoustic backscatter

I. INTRODUCTION

Marine debris are commonly vaguely defined as being any man-made object discarded, disposed of, or abandoned that enters the coastal or marine environment [1]. They can be made of a variety of materials, directly related to those commonly used by our society: plastics, from industrial products (strapping bands, resin pellets, plastic sheeting) to common domestic material (bags, bottles), as well as other materials (metal, styrofoam, rubber, glass) that, like plastic, have a wide range of uses [2]. They tend both to break down into smaller fragments and to be worn away, but they do not biodegrade entirely. Marine debris span in size from the millimetric size of resin pellets to entire sunken vessels [1]. Thousands of abandoned and derelict crafts are presently close to the shoreline, in a multiplicity of states (e.g., semi-submerged in the intertidal zone, stranding on reefs or in marshes) [3]. When present in protected areas (e.g., lagoons), these shipwrecks may persist for years; while exposed environments can force their disintegration, and generated litter may be distributed widely through multiple habitats [2, 4]. Marine debris are commonly classified by source type into ocean-based and land-based [1]. The primary ocean-based sources are vessels (e.g., derelict fishing gears such as nets, traps, buoys, lines lost by commercial fishing vessels and recreational boats, entire containers from cargo ships in rough seas), but stationary platforms also play an important role since all items lost from these structures become litter (e.g., hard hats and gloves, storage drums). However, the largest part of debris along the shoreline comes from land-based sources [1].

Debris may be blown, swept, and washed out to sea after their accidental or intentional disposal as domestic or industrial wastes on land or in streams. In normal conditions, rain and snow-melting waters are the typical means by which these materials are carried to a nearby river or canal, or even directly to the ocean. Natural disasters such as hurricanes, tsunamis, mudslides and floods are usually coupled with devastating effects such as heavy rains, flooding, strong winds, high waves, and storm surges [5, 6]. The direct result on marine debris is a peak rate of new depositions (in both intertidal and subtidal areas), an additional problem for regions already impacted by a natural disaster. In fact, this abnormal amount of marine debris may create threats to navigation, fishing activities, recreation, sensitive ecosystems, and generally to the environment and human safety [1, 6]. Effectively and quickly processing large amounts of hydrographic data collected using commercial systems for detection of marine debris would be highly advantageous to the necessary remediation operations [7].

A coherent framework for such a challenging task must take into account a series of different aspects and as much available information as possible, from the spatial relationship between the marine debris distribution and explanatory variables to an effective way to merge the results of different detection algorithms, required as a consequence of the vague definition in size, shape and material of the investigated targets. At the same time, some degree of modeling and approximation to make the analysis computationally attractive and sufficiently effective in practice is also required [8, 9]. This work begins by analyzing the marine debris distributions in recent available data sets, from which a possible predictive modeling was outlined. The predictive step provides the initial state for a Bayesian spatial hierarchical model, but can also be used as a post-hurricane survey planning tool. For the detection, a target model was built postulating a simplified description of the debris properties, and a set of detection algorithms were specifically targeted to different possible characteristics of marine debris, detecting discrete objects which differ (e.g., protrude) from the surrounding seafloor, being close or connected to the bottom. The scope of these algorithms was constrained to analyze products commonly available in existing post-processing software (mainly, bathymetric digital terrain models and backscatter mosaics with several associated data sets, such as statistics derived from the core data, or during construction) so that the technique may

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be quickly inserted into existing workflows, which eases resource management in a response situation. Finally the paper provides an example of detector outcomes, based on survey data collected after Super Storm Sandy, to evaluate the effectiveness of the proposed technique. In concluding, we discuss a synthesis of the results obtained, identifying future research imperatives.

II. Data and Methods

A. *Case Studies and Data Sources*

Super Storm Sandy was a natural disaster with unusual characteristics [10]. Started as a classical late-season hurricane in the Caribbean Sea, a complex evolution made Sandy grow considerably in size, moving parallel to the coast of the United States (Fig. 1). After turning northwestward over much cooler waters, Sandy weakened and started to lose its tropical characteristics about 45 nautical miles off Atlantic City, becoming an extra-tropical cyclone (that is, relying mainly on baroclinic processes), to make landfall near Brigantine, NJ, around 7:30 p.m. on October 29, 2012. Because of Sandy's unusually large size, the New Jersey and New York coastlines were hit by a catastrophic storm surge, accompanied by powerful damaging waves and enhanced by the Fall full moon period. The impacts of Sandy were widespread, with at least 650,000 houses damaged or destroyed, cars tossed about, boats pushed well inland from the coast [10]. Sandy represented a massive source of marine debris deposition for impacted coastal areas. However, being relatively close in time, Hurricane Irene most likely also influenced the debris distribution [11].

Two marine debris data sets available in the Sandy area are used in the present work:

- The NOAA Marine Debris Program (MDP) dataset, mainly focused on intertidal coastal areas (hereafter, SSS-ID), which was based on NOAA NGS imagery acquired during post-storm overflights, and follow-up shoreline survey [12]. The data set is made up of almost 70,000 debris records: 52% identified via automated Object Based Image Analysis (OBIA) [13], and the remaining targets marked via manual heads-up digitization by imagery analysts.
- NOAA's Office of Coastal Survey (OCS) dataset, which is a growing collection of subtidal marine debris (SSS-SD), mainly based on several surveys using a variety of acoustic sensors (e.g., Multibeam Echo Sounders, Side Scan Sonars) performed by contractors. This preliminary data set (some processing is still ongoing) was retrieved directly from NOAA OCS.

The third analyzed data set is the one collected by the Gulf of Mexico Marine Debris Project (GOMMDP), a large collection of marine debris items related to Hurricanes Katrina, Rita and Ivan, and identified via side scan sonar during several surveys conducted in 2006 [14]. There are several relevant differences between the GOMMDP and the Sandy areas. The former project area is quite flat, while in comparison the latter is characterized by moderate bathymetric and topographic relief (Fig. 1). The complex geography of New York Harbor and Long Island Sound generated quite distinct patterns for the maximum elevation of storm surge and peaks of strong winds; while they are almost coincident in the area impacted by Katrina. Another relevant difference is that Sandy affected one of the most densely populated areas along the East Coast, while much of Katrina effects were on rural or low-density suburbs [10, 15].

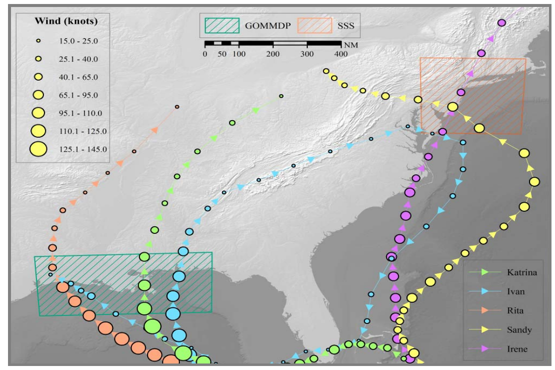

Fig. 1. Study areas, and the best tracks (associated with peak winds) of the five hurricanes of interest.

These three data sets were used for the predictive step, while survey data collected after Sandy, in the Redbird Reef area, DE and Jamaica Bay, NY, were used to test the fusion approach for the detector.

B. *Spatial Analysis*

Spatial data are often characterized by a phenomenon, known as spatial auto-correlation (SAC), that occurs when the values of variables sampled at nearby locations are not independent from each other [16]. In marine debris data, SAC may arise from a multitude of possible causes, both from intrinsic processes, such as debris size and target-seafloor interactions, and in response to unknown (or partially known) environmental drivers, e.g. non-linear relationships between predictors and dependent variables modelled erroneously as linear, or failure in accounting for an important environmental determinant that is itself spatially structured [17]. SAC often poses serious shortcomings for hypothesis testing and prediction by violating the assumption of independently and identically distributed errors required by most commonly-used statistical procedures [18]. In the absence of a perfectly correctly specified model, SAC cannot be accounted for by non-spatial models [19], and some kind of correction, such as the one introduced by auto-covariate regression, is required [20]. However, SAC may also be seen as an opportunity since it provides useful information for inference of a process from patterns [21].

The distribution of marine debris density over a seafloor area is a spatially-distributed stochastic phenomenon. The density values represent a set of variates, and we want to decide whether there is any evidence that these variates are spatially correlated. However, real scenarios such as the case studies usually present a quite complex hierarchical structure that cannot be simply modeled as regular or clustered point processes, and they may exhibit different spatial pattern characteristics at different scales [22]. The verification of the hypothesis that the debris locations tend to cluster rather than following a complete spatial randomness (CSR) process, under which their patterns are realizations of a Poisson point process, is thus an important preliminary step. Dedicated methods can be classified as global (throughout the whole study region) or local. As global methods, there are several established procedures (global Moran's I plots, Geary's C correlograms and semi-variograms), in which a measure of similarity or variance of data points is plotted as a function of the distance between them, to check whether spatial correlation is likely to impact the data analysis [23]. Moran's I varies between -1 and $+1$, and a value close to 0 indicates a random pattern or absence of spatial autocorrelation [24]. Calculation of the *z-score* provides a means to evaluate the intensity of spatial clustering, looking for clustering lags with statistically significant peak *z-scores* (based on a randomization null hypothesis). Given the kind of pattern of this study, the focus is on a quite local level of clustering, and this method allows the correct size of the analysis to be determined from the data. Local methods such as Local Indicator or Spatial Association (LISA) and hot-spot analysis, when used in conjunction with global Moran's I, deepen the knowledge of the processes that give rise to spatial association, enabling the detection of local pockets of dependence that may not show up when using global methods [25]. The Local Indicator of Spatial Association (LISA) is a local Moran index proposed by Anselin [26]. This method highlights clusters as well as possible outliers, a low value surrounded by high values (low–high) or a high value surrounded by low values (high–low). The hot-spot analysis identifies local spatial clusters of statistically significant high (hot spot) and low (cold spot) number of debris for a grid cell by calculation of the Getis-Ord Gi* statistic [27].

The popular K-means algorithm was also adopted as an exploratory tool, applying a cluster analysis to identify possible structure between the available data in the absence of category information [28]. The selection of the number of groups was based on the pseudo F-statistic, a ratio reflecting within-group similarity and between-group differences [29].

C. Predictive Model

SAC occurs at all spatial scales (from meters to dozens of kilometers) for a whole suite of reasons. Since these reasons are mostly unknown, one cannot readily derive a spatial correlation structure for an entirely new and unobserved area, although it is possible to derive predictions by interpolation for missing data within the study area (i.e. by using a Gibbs sampler) [30, 31]. When models are projected into different areas the handling of spatial auto-correlation is quite problematic, sometimes even impossible. Extrapolation in space can only be based on the coefficient estimates, not on the spatial component of the model [8, 24]. Extrapolation is further complicated by model complexity: the use of non-linear predictors and interactions between environmental variables usually increases model fit, but with the price of compromising model transferability in time and space. Given such intrinsic limitations, a predictive model was created with the main aim of providing a reliable initial state to the Bayesian detector; however, the evaluation of areas where the presence of marine debris is more probable, coupled with considerations related to the economic relevance of specific waterways, may also help to effectively prioritize the areas to survey and the data to process, speeding up identification of detected possible targets and their eventual removal. A limited number of predictive debris models have been recently developed: the web-based HurDET model [32]; USACE HAZUS-MH models [33, 34]; and, the Marine Debris Distribution model of the Gulf of Mexico, from the NOAA Marine Debris Program (MDP) [6]. While the first two are focused on terrestrial debris, some of the findings and the results from the MDP model have been adapted and incorporated in the present model, attempting both to generalize the approach (to increase flexibility) and to cast the modeling results to feed a probabilistic algorithm for marine debris detection.

A list of possible marine debris predictors (Table I) was created following an intuition criterion, coupled with comparison with existing similar work and data availability. This latter criterion is for model flexibility, to avoid a model based on peculiar predictors that, although highly explanatory of debris presence, will not be likely available in case of natural disasters in different areas, as well as in the immediate proximity of the event. The selected predictors can be clustered in two groups: related to the storm energy (wind, storm surge, bathymetric profile, etc.) and capturing the spatial distribution of debris sources (concentrations of highly populated human areas, waterways, etc.). The intuition behind such a choice is that coastal urban areas impacted by high storm energy should have larger amounts of anthropogenic debris, due to higher potential for debris creation and mobilization.

TABLE I. PROXY SOURCE FOR MODEL PREDICTORS

Data Product	Predictor	Source
H*Wind Surface Wind Analysis	Wind	NOAA
Experimental Extratropical Surge and Tide Operational Forecast System (ESTOFS)	Storm surge	NOAA
NGDC 3-Arc Second Coastal Relief Model	DEM	NOAA
International Best Track Archive for Climate Stewardship (IBTrACS)	Hurricane best-track	NOAA
Global Self-consistent, Hierarchical, High-resolution Geography Database (GSHHG)	Shoreline	NOAA
Natural Waterway Network	Waterway	USACE
Topologically Integrated Geographic Encoding and Referencing (TIGER)	Population	CENSUS

The wind-based predictor was created by summarizing into a single layer, only representing the peak intensity, the surface wind analysis of tropical cyclones produced by the NOAA Hurricane Research Division as part of the H*Wind Project [35], a project that merges a variety of coastal and inland data from land, space, and marine platforms. Data from the Extratropical Surge and Tide Operational Forecast System [36], a new generation hydrodynamic modeling system using the ADvanced CIRCulation model, was used as storm surge predictor. The NGDC 3-Arc Second Coastal Relief Model [37], integrating bathymetric and topographic information from a variety of data sources, was used to explore the relationship between debris and depth. The best tracks for the hurricanes in the study have been retrieved from NOAA's International Best

Track Archive for Climate Stewardship (IBTrACS) project [38], collecting the historical tropical cyclone best-track data from all available Regional Specialized Meteorological Centers (RSMCs) and other agencies [39]. The distance of each cell in the lattice grid has been calculated having as reference the World Vector Shorelines (WVS), present in the Global Self-consistent, Hierarchical, High-resolution Geography Database (GSHHG) [40], while for the waterways the USACE Natural Waterway Network was adopted [41]. Finally, a population index was derived from the 2010 census Topologically Integrated Geographic Encoding and Referencing (TIGER) product [42].

A classic Ordinary Least Squares (OLS) [24] was adopted to create an equation relating marine debris density (dependent variable) to the selected set of explanatory variables. Exploratory regressions were used to find a good specified model by evaluation of all the different possible combination of explanatory variables, balancing statistical significance, redundancy and multi-collinearity [8, 9, 24]. Such a balance was mainly evaluated by comparison of Adjusted R-squared, Akaike information criterion (AIC) and Variance Inflation Factor (VIF) values [8, 9].

D. Detection Algorithms

A comparison of the SSS-SD data set and the original survey data was used to estimate the criteria used by the analyst for defining the presence of a possible marine debris. From the analysis of the targets selected so far within the SSS-SD data set, several common selection patterns emerged [7]. For instance, a first group containing a rounded shape and/or a jump in seafloor reflectivity was common to many of the several hundred targets examined. A second group was based solely on bathymetry evaluation. A third group comes from an integrated analysis of the Digital Terrain Model (DTM) and the acoustic backscatter. Finally, although such data can now be readily collected on many systems, there are no examples of debris selection based on water column data, although the extent of availability of this data (and appropriate tools) to the observers is unknown. It appears that operator debris detection was mainly based on the bathymetry and the reflectivity of the seafloor, assuming any deviation from the 'natural average background' as hints of possible debris. From that consideration, and given the intrinsic complexity of the targets, it is likely that a single algorithm will not be successful for robust marine debris detection. The proposed solution is therefore based on multiple algorithms to process different sources (at this stage, mainly bathymetry and backscatter from acoustic systems, but extendable to water column data, as well as lidar data), fused together so as to be adaptive to the environment, the context, and *a priori* knowledge (if available) of the possible targets. The goal is to use a collection of algorithms working at different levels (e.g., through per beam, single swath, snippet and pixel level operators), which are then fused by the core engine. One of the primary advantages of this approach is operating over different data with independent algorithms can reduce inter-algorithm cross-correlation and therefore the probability of false alarm [7].

For the backscatter mosaic, as in many existing algorithms, target detection is based on the observation that denser material (often anthropogenic) makes debris returns much stronger than the surrounding background. However, the often used approach to object detection through simple thresholding (e.g., based on the premise that on a mosaic the object return is brighter than the background) was modified since it tends to fail when the background is textured (i.e., detectors are not aware of image correlation). This algorithm is based on an acoustic backscatter mosaic, and takes advantages of previous NOAA-sponsored work at the Joint Hydrographic Center to properly geometrically and radiometrically correct the collected data [43]. The resulting mosaic is segmented into areas with similar reflectivity values through a clustering analysis, and a histogram of backscatter values as a function of angle of incidence is then computed for each clustered area (effectively forming a bivariate histogram). A simple Bayesian classifier is subsequently used to identify areas in each segment where the statistics of a small window do not match that of the overall background distribution (as characterized by the appropriate marginalization of the histogram constructed previously). Areas of low probability of background membership are identified as potential marine debris. Subsequent edge detection and hierarchical filtering are applied to remove misdetections along the mosaic boundaries [7]. The backscatter information content, as variable angular response return, is also used in a model-based detection algorithm. The angular response for each acoustically clustered area (i.e., detecting anomalies from the average angular response, which is quite different from the mosaic response where angular differences are removed), and evaluation of the half-swath patch (i.e., stacking a certain number of successive pings to stabilize the statistics and reduce the noise), again looking for anomalies in the angular response of the immediate area [7].

For the bathymetric DTM, a few spatial indices were used as proxies for any discontinuity and, thus, a possible target. In particular, a particular promising algorithm is based on the Combined Uncertainty and Bathymetry Estimator (CUBE), a weighted surface-construction algorithm for automatically that processes big and dense bathymetric data set, and that addresses issues as efficiency, objectivity, robustness and accuracy [44]. Based on available soundings, the nodes independently assimilate propagated information to form depth hypotheses which are then tracked and updated on-line as more data is gathered. CUBE manages groups of soundings that are mutually inconsistent, but internally consistent, by segregating them in sacrificial alternate hypothesis, avoiding cross-contamination of estimates [44]. The state of knowledge about the data is summarized for each estimation node by a list of depth hypotheses (Multiple Hypothesis Tracking). This work explores the use of CUBE's auxiliary products for marine debris detection. The map of hypothesis counts clearly shows areas of difficulty in the gridding process, and, together with CUBE's estimate of the correctness of the hypothesis selected by the disambiguation engine (hypothesis strength) [45], may be used as a proxy for debris presence. Low values of hypothesis strength are used to assess a node depth reconstruction that is sufficiently robust to be reliable [46].

For both backscatter and bathymetry, the adoption of classical estimation techniques usually generates point estimate or a confidence interval, which becomes important when fusion of target information coming from different products is attempted. In order to provide appropriate distributions for exploitation, Bayesian methods were adopted since they permit use of multiple-source asymmetric and discontinuous posterior distributions that may be carried into further analysis. A hierarchical scheme is proposed where a series of modeling tasks are implemented through a probabilistic model, casting the debris detection problem as one of estimating properties of the posterior distribution describing the probability of objects occurring given the observed data products.

E. Fusion Approach

The proposed fusion approach provides a means to statistically merge together the output of a set of detection algorithms, each of them consuming hydrographic data products (e.g., bathymetric surfaces, backscatter mosaics, seafloor characterization analyses). Since the detector has been developed with the task of detecting the presence of marine debris over a surveyed area, this task can be basically reduced to a classification problem based on only two classes. After having discretized the surveyed area using a regular lattice, the classifier maps each cell of the lattice to one element of the set $\{t, n\}$, respectively representing target and not-target labels. Similar to other existing classification models, the classifier produces an intermediate step that estimates membership probability to the 'target' class for each cell. The application of a different threshold to such an estimate can be used to tune the classifier behavior, directly influencing its balance between hit rates and false alarm rates. For notational clarity, the label set $\{Y, N\}$ is specifically introduced for the detector output, to distinguish predictions from the actual class. The detector may reach four possible states, as summarized using a two-by-two matrix, called contingency table, in Fig. 2.

		Actual Labels	
		t	*n*
Detector Labels	*Y*	***TP*** *True Positives*	***FP*** *False Positives*
	N	***FN*** *False Negatives*	***TN*** *True Negatives*
		P *Total Positives*	***N*** *Total Negatives*

Fig. 2. Contingency table and notations adopted for the marine debris detector.

The classifier states can be combined in various classification metrics, such as:

- The *true positive rate* (*TPR*), or *sensitivity*, evaluated as

$$TPR = TP / P \tag{1}$$

  where P represents the 'real' total positives.

- The *specificity*, directly related to the *false positive* (or *false alarm*) *rate* (*FPR*),

$$spec = TN / (FP + TN) = 1 - FPR. \tag{2}$$

The performance of the proposed detector can be depicted using two-dimensional Receiver Operating Characteristics (ROC) graphs [47]. On these graphs, a diagonal line ($y = x$) is added to represent the strategy of randomly guessing a class. A single scalar representing the portion of the area of the unit square, called the Area Under the Curve (AUC), is commonly used to compare classifiers. Since random guessing produces an area of 0.5, no realistic classifier should provide a value less than 0.5.

The debris data are necessarily categorical: either binary (presence/absence) or abundance (number of objects at a given location). This work focuses on binary data, seen as the result of the fusion approach, that may be easily fitted using logistic regression, which is straightforward to implement using standard maximum likelihood [48]. However, like all linear models, logistic regression is incompatible with SAC observations since it assumes independence of errors. Thus, among several possible approaches for modeling autocorrelation in binary data, the auto-logistic approach [17, 49], that extends the logistic model to allow dependence between nearby observations [17], was selected. Common past objections against the use of auto-models seem to be due to incorrect model implementations, providing a general conclusion of validity for auto-model analysis of SAC data [50].

The full likelihood for the auto-logistic model is known analytically only within a normalization constant [51], an analytically intractable function of the regression parameters. This issue has driven the development of an approximation scheme known as the maximum pseudo-likelihood estimate method (MPLE). Although auto-covariate term are included in the regression, MPLE assumes that the sites are independent for the purpose of constructing the likelihood function (that simplifies to a simple product form). Several researchers have observed inaccuracy (e.g.,. overestimation of intrinsic auto-correlation in data with strong intrinsic SAC) resulting from MPLE application [52]. Thus, a simple Bayesian implementation of the auto-logistic model was adopted, avoiding MPLE but adding a computation burden. This solution can be simultaneously used for model fitting, based on covariates, and for making predictions about unsurveyed parts of the study area. In several recent examples, the auto-logistic model has been implemented in a Bayesian framework adopting the MCMC methodology first described by Geman and Geman [53]. This methodology constructs a non-normalized posterior distribution for the unknown parameters and any missing observations (which are treated as unknown parameters). The resulting distribution, conditional on the observations, is sampled according to one of the possible MCMC procedures (e.g., the Gibbs sampler) that guarantee that certain sequences of dependent samples (Markov chain) will converge to the target distribution. This Bayesian approach allows for a more flexible incorporation of possible complications (observer bias, missing data, and different error distributions) at the expense of more computational-intensive requirements.

III. Results

A. Exploratory Analysis of Available Data

The global Moran's I statistic, which is used to test the null hypothesis that the spatial autocorrelation of a variable is zero, was applied to the study case data sets. The results are presented in Fig. 3, with the first peak of *z-score* plotted as a red dot.

The results from LISA and hot-spot analysis are presented as Pane A and B in Fig. 4 for the GOMMDP data, in Fig. 5 for the SSS-ID data, and in Fig. 6 for the SSS-SD data; while Pane C was used to spatially identify the areas resulting by the grouping analysis, performed using K-mean algorithms and based on the pseudo F-statistic to identify the parameter for the number of groups: two for GOMMDP and SSS-ID data sets, three for SSS-SD data set. For this last, a plot with the resulting inter-group relationships is presented in Fig. 7.

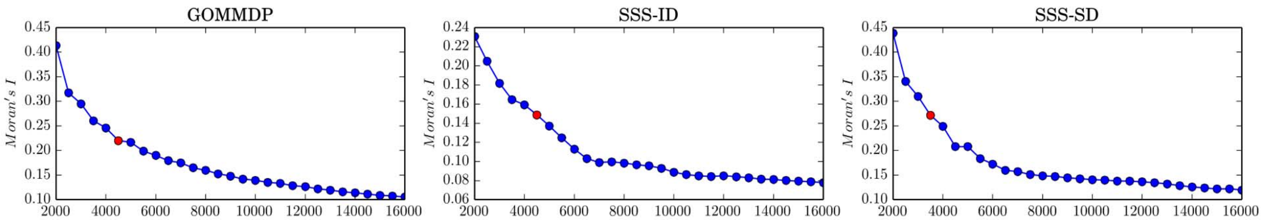

Fig. 3. Global Moran's I statistics (with, in red, the first peak of the associated *z-scores*) calculated for the case study data sets.

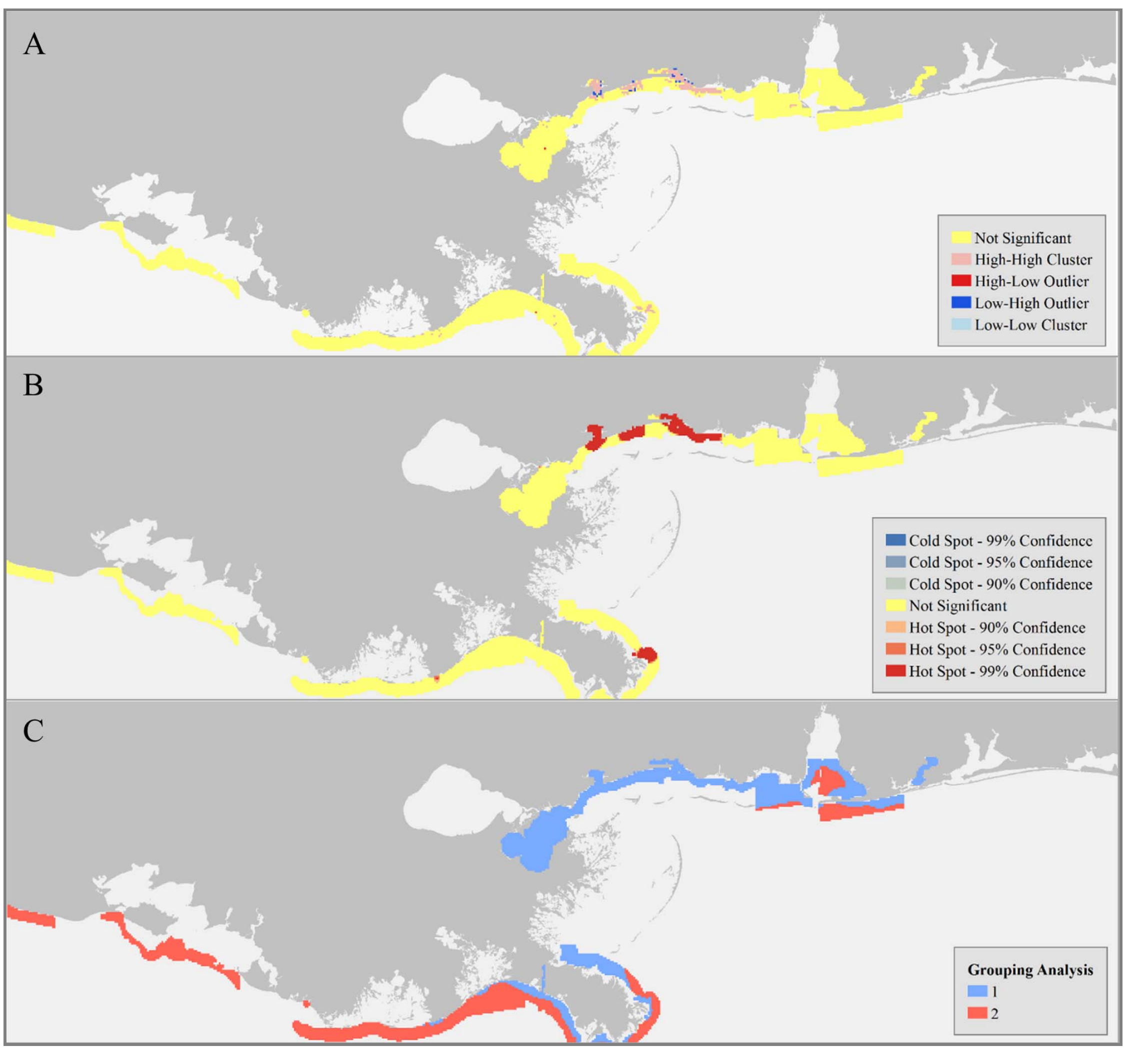

Fig. 4. Local Moran's I statistics (pane A), hot spot analysis (pane B), and grouping analysis (pane C) for GOMMDP data set.

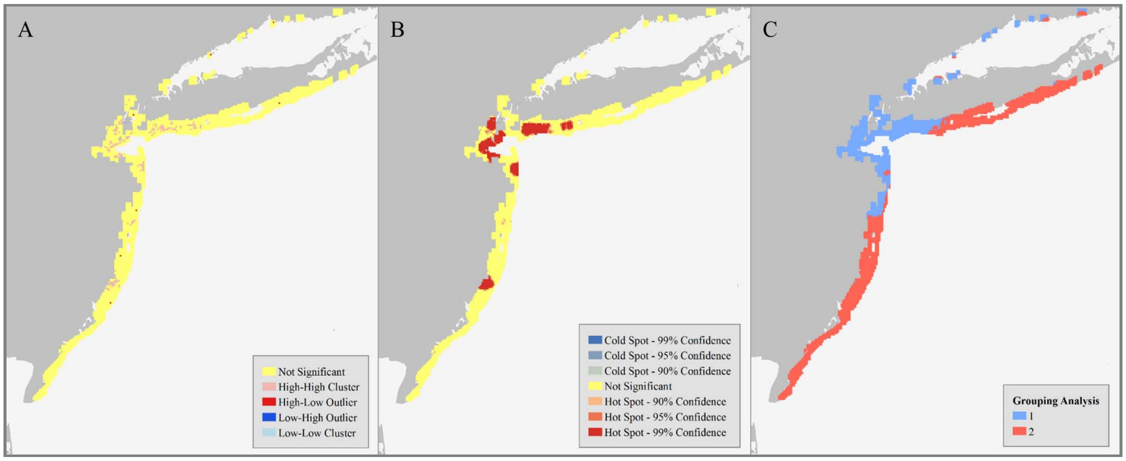

Fig. 5. Local Moran's I statistics (pane A), hot spot analysis (pane B), and grouping analysis (pane C) for SSS-ID data set.

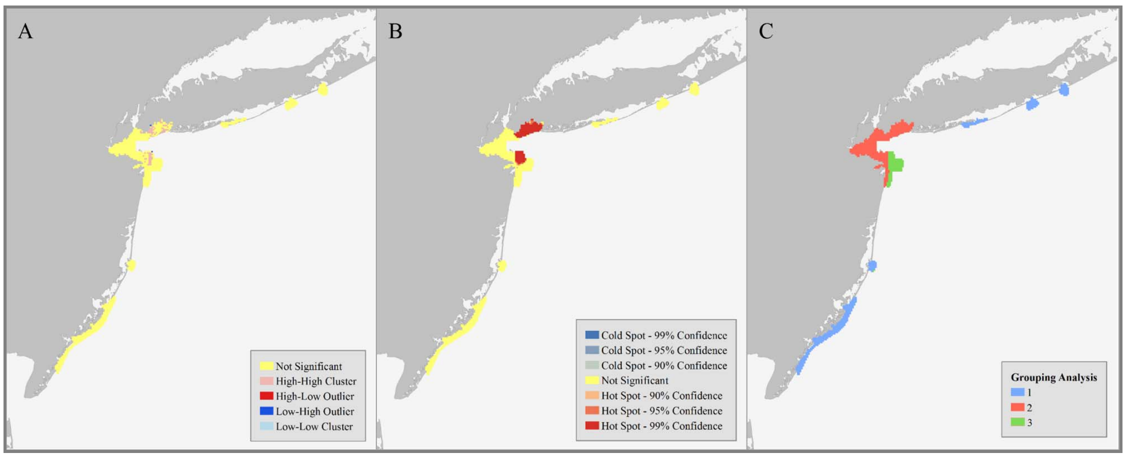

Fig. 6. Local Moran's I statistics (pane A), hot spot analysis (pane B), and grouping analysis (pane C) for SSS-SD data set.

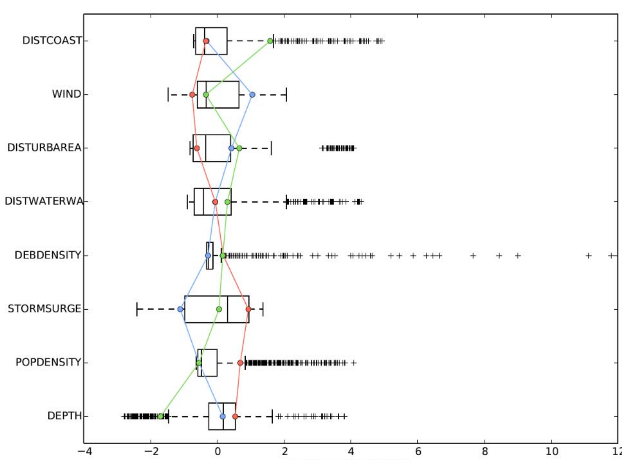

Fig. 7. SSS-SD grouping analysis outcomes between debris density ("DEBDENSITY") and predictors: distance from the shoreline ("DISTCOAST"), maximum wind ("WIND"), distance from the urban area ("DISTURBAREA"), distance from waterway ("DISTWATERWAY"), maximum storm surge height ("STORMSURGE"), population density index ("POPDENSITY"), and average depth ("DEPTH").

B. Predicted Debris Distribution

After an exploratory regression based on the seven predictors listed in Table 1, both study areas obtained similar results indicating that storm surge, population density index, and distance from urban areas are quite good predictors of marine debris presence (R-squared higher that 0.5). The addition of other available predictors does not provide significant contributions to the R-squared values, adding decrements in terms of AIC and VIF values. Using the resulting model parameter coefficients, a prediction of debris distribution for the areas covering is presented in Fig. 8, for the SSS-SD data set, and in Fig. 9, for the GOMMDP data set.

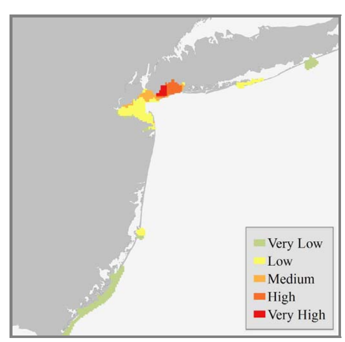

Fig. 8. Predicted distribution density of marine debris in the SSS study area.

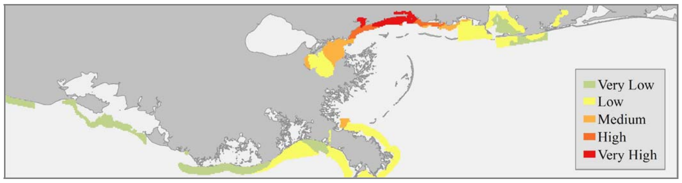

Fig. 9. Predicted distribution density of marine debris in the GOMMDP study area.

C. Detection Performance

The detection outcomes based on auto-logistic and logistic regressions have been compared. The comparison has been performed separately on two data sets: a first data set was artificially created, injecting SAC as described in [50], and a second set of outcomes was obtained from the application of the detection algorithms to real hydrographic products. The real products were based on data collected after the Super Storm Sandy event. The resulting ROC graphs for both data sets are presented in Fig. 10. The graphs for the artificial data set present AUC values of 0.923 (logistic regression) and 0.940 (auto-logistic regression); while, for the real survey data set, AUCs of 0.862 and 0.880 characterize the logistic and the auto-logistic regressions, respectively.

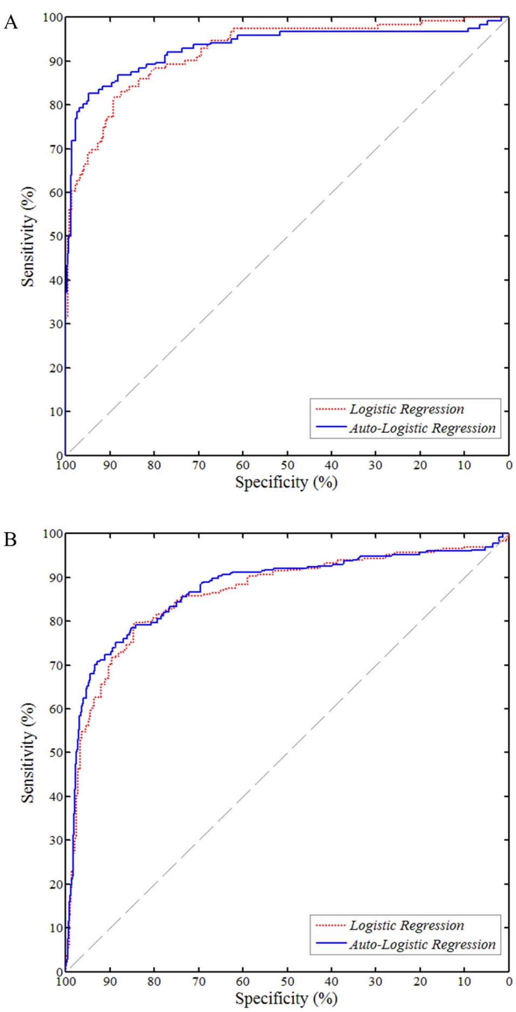

Fig. 10. ROC curves for artificial data (pane A) and real survey data (pane B).

IV. Discussion

The resulting global Moran's I values show a similar trend for the GOMMDP and the SSS-SD data sets, with peaks at 3.5 and 4.5 km respectively, but lower values in the SSS-ID (although with a consistent peak at 4.5 km). Such a difference could be justified by the fact that restoration efforts are more likely to have been applied on the intertidal zones due to their accessibility. The Getis-Ord Gi* test identified several clusters of points that have higher values than expected by chance. For the GOMMDP dataset, the analysis results suggest a relationship between the hurricane Katrina track, the urban areas and hot-spots of marine debris density (Fig. 4). Several hot- and cold-spots are also present for the Sandy datasets (intertidal debris in Fig. 5, and subtidal debris in Fig. 6), although relationships with tracks and urban areas are less visually evident. The results from the hot-spot analysis are compatible with the LISA outcomes, and only a very limited number of possible outliers are present. An interesting result from the grouping analysis is the different number of groups (three rather than two) for the SSS-SD data set. As is clear in Pane C of Fig. 6, the anomaly is spatially localized (the results of the grouping analysis are expanded in Fig. 7) and almost exactly matches with an area assigned to a specific contractor. Thus, it is possible to speculate that this is most likely due to different criteria followed in the target detection analysis (most strict). Consequently, the debris distribution in this area was clipped from the remaining analysis (although it is worthwhile of additional future investigation). The evaluation of whether a debris distribution exhibits a spatial clustering pattern implies the question if elevated debris rates arise simply by chance and thus have no predictive utility. Since the case studies show statistically significant patterns, marine debris density warrants study since it can be used, e.g., to identify hot spots that can be used by post-hurricane survey planners to prioritize and target the data collection on limited areas.

Two key elements of the developing marine debris detector have then been presented: a predictive model, providing an initial state to reduce the burn-in phase; and a fusion approach based on auto-logistic regression, to improve the classifier performance. Expected trends are higher presence of debris in areas that received during the hurricane both higher wind energy and storm surge water elevations, and that are proximal to more developed and populated urban areas. The predictive model was developed thanks to the availability of several data sources, variously related to marine debris, collected and made publicly available after hurricanes Ivan, Katrina, Rita, Irene and Sandy. The analyzed debris data sets represent two case studies, with distinct peculiarities. The future addition of similar rich databases will surely help to obtain a clearer picture of how individual characteristics of hurricanes interact with human land use to lead to various types and degrees of marine debris deposition. In fact, this deposition may or may not occur, or occur to varying degrees, depending upon individual hurricane characteristics (e.g., category, breakpoint, maximum wind speed, height of storm surge, and path after landfall). Landfall in a populous area, a post-landfall trajectory upriver toward a headwater region, or a relative slow speed of hurricane passage are just some of the many variables that, leading to increased damages, can carry to a massive creation of marine debris. The different intensities and tracks for the hurricanes affecting the study areas are clear examples of how each storm-like event has its own peculiarities (Fig. 1). A practical difficulty in common to these and similar data sets is the complexity involved in distinguishing between anthropogenic and natural, storm-generated and pre-existing targets. In order to make the analysis possible, it was assumed that each of them provides a representative picture of the distribution of storm-related and anthropogenic marine debris. Furthermore, the model also relies on the assumption that the distribution of marine debris objects is essentially static, even months after the event occurred, in order to use data sets collected after a variable amount of time since the event. This is increasingly likely to be faulty in function of the time passed since the event or, for instance, in case of another storm-like event occurred. Furthermore, the seven adopted predictors do not directly capture all the possible causes of concentrations of marine debris: for instance, areas with particular activities (e.g., recreational marinas), specific land use in the neighborhood such as dumping areas, and strong energy impacts of wave run-up effects. Additional predictors capturing such causes will be evaluated in future studies, with the challenging criterion to maintain model's spatial portability.

Hydrographic data processing for target detection is usually subjective and time consuming, so increasing the automation of the process and thus reducing its subjectivity can greatly assist in planning for debris removal. For the fusion approach, we investigated covariate influence in logistic and auto-logistic analyses, both using the same covariates. The auto-logistic implementation outperformed the basic logistic model in removing residual auto-correlation. Thus, the auto-logistic model provides a better description of the observed clustering of objects, since the logistic model cannot represent clustering at all unless it is present in the covariates. Furthermore, ROC plots (Fig. 10) indicates better overall predictive performance by the auto-logistic model due to much higher true positive rates at small false positive rates, although the logistic model slightly outperforms at low (artificial data set) and intermediate (real data set) specificity. Classifiers appearing on the left-hand side of an ROC graph (near the Y axis), are usually evaluated as more "conservative", since they make positive classifications only with strong evidence (so they make few false positive errors) [47]. Since the marine debris detection domain is usually dominated by large numbers of negative instances, performance like the auto-logistic regression becomes more interesting. Similar tests with data sets collected over different areas and using various sensors will be applied to verify the robustness of the approach.

The adopted Bayesian approach allows for a more flexible incorporation of possible complications (observer bias, missing data, and different error distributions) and prior beliefs at the expenses of higher computational-intensive requirements. Furthermore, a good understanding of the influence of prior distributions and convergence assessment of Markov chains is crucial to properly evaluate the methodology results. The scalability of the fusion technique permits its straightforward extension to additional detection algorithms for *ad-hoc* created data products, with expected improvements both in robustness against outliers and in detection performance. Given such a framework flexibility, we are currently working on extending the detector with a set of *ad hoc* hydrographic products. Although the probability of false alarm based on a combined analysis of multiple data sources is expected to be generally lower than when a single source is used, there are particular cases where a particular object might only be observable within a single data source. For example, a semi-buried target, or one with a flattened shape, might only be visible through acoustic backscatter. A careful analysis of the benefits of different algorithms and different data sources is therefore indicated as future research imperatives.

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