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Emergency Evacuation Behavior in Small Island Developing States: Hurricane Irma in Sint Maarten

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Abstract: Disasters triggered by natural hazards are becoming more frequent and more intense, causing damage to infrastructure and causing loss of life. One way to reduce disaster risk is by evacuating the hazardous area. However, despite the amount of literature that exists on evacuation behavior, there is still a lack of agreement on which variables can be used as predictors for individuals (or households) to actually evacuate. This lack of agreement can be related to the many variables that can affect the evacuation decision, from demographics, geographic, the hazard itself, and also local or cultural differences that may influence evacuation. Hence, it is essential to analyze and understand these variables based on the specifics of a case study. This study aims to find the most significant variables to be used as predictors of evacuation on the island of Sint Maarten, using data collected after the disaster caused by Hurricane Irma in September 2017. The results suggest that the variables gender, homeownership, percentage of property damage, quality of information, number of storeys of the house, and the vulnerability index are the most significant variables influencing evacuation decisions on the island. We believe the results of this paper offer a clear view to risk managers on the island as to which variables are most important in order to increase evacuation rates on Sint Maarten and to plan more efficiently for future evacuations. In addition, the variables found in this study have the potential to be the base information to set up, validate, and calibrate evacuation models.

Keywords: evacuation; predictors of evacuation; hurricanes Irma; binomial logistic regression; risk management

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1. Introduction

The severity and frequency of disasters related to weather events, such as hurricanes, floods, and storms, have been on the rise [1,2]. This trend is evident in the increasing economic losses associated with the reported events. During the period 1998–2017, there was a 49% rise in average economic losses compared to the previous decades [3]. Furthermore, the expansion of urban areas, particularly those situated near coastal regions, is amplifying the vulnerability of both populations and infrastructure to the impacts of extreme climate events [4,5].

The year 2017 provided clear evidence of the impact of climate change on disasters. During that year, the Atlantic hurricane season experienced a notable surge in activity, with 17 named storms, 10 hurricanes, and 6 major hurricanes [6]. Among them, Hurricane Irma stood out as one of the most destructive storms on record. Making multiple landfalls, including four as a Category 5 hurricane, Irma caused catastrophic devastation to the Small Island Developing State (SIDS) of Sint Maarten. The island suffered 14 confirmed fatalities and incurred losses equivalent to 797% of its GDP [7,8]. The significant impact of Hurricane Irma on Sint Maarten underscores the urgent need for effective disaster risk management to safeguard the island's sustainability and mitigate the losses caused by natural hazards.

One alternative to reduce risk from disasters triggered by natural hazards is to minimize the exposure of individuals and their assets to potential hazards. This can be achieved by implementing timely and effective protective measures. Among the various available options, evacuation from high-risk areas has emerged as one of the most commonly used effective strategies [9]. However, despite extensive research on evacuation since the early 1960s, instances of failed evacuations occur annually worldwide, resulting in devastating consequences. Some examples of such events are Hurricane Katrina in the USA in 2005, Hurricane Irma across the Atlantic basin in 2017, and other similar events. Thus, gaining a comprehensive understanding of evacuation behavior becomes extremely important in order to mitigate loss of life and develop improved and realistic evacuation plans [10]. Evacuation behavior during water-related disasters, including hurricanes, tsunamis, and floods, is influenced by a multitude of factors that span from individual variables to group decision-making processes, and others related to the type and intensity of the hazard or to the geographical location [11].

A wide number of individual characteristics play a role in shaping evacuation decisions. Demographic factors such as age, gender, and health conditions can impact an individual's ability or willingness to evacuate. Socio-economic characteristics, including income, education, and access to resources, can also influence evacuation behavior. Evacuation decisions are often influenced by social dynamics and group decision-making processes. Factors such as social networks, family structures, and community cohesion can impact evacuation behavior. People often seek information, support, and validation from their social circles, which can affect their decision to evacuate or stay. Cultural beliefs, values, and norms also shape collective decision-making processes during water-related disasters. In a similar way, the characteristics of the specific water-related hazard, such as the type and intensity, the perceived threat level, potential for destruction, and the level of uncertainty associated with the hazard can all influence the evacuation decision-making processes.

The understanding of which variables are good predictors of evacuation is then a crucial element in the disaster risk management cycle [12]. To the best of our current knowledge, there has been no exclusive research conducted on evacuation predictors in the context of SIDS. Additionally, the existing studies conducted in other urban environments exhibit significant variability in determining the parameters that promote or hinder evacuation. This emphasizes the necessity of conducting a study similar to the one presented in this research. On one hand, such a study would facilitate resource optimization by enabling the improved design of instruments, such as surveys, for collecting field data. On the other hand, it would assist risk managers in comprehending the elements that require special consideration to enhance evacuation responses and thereby mitigate disaster risk [13,14]. Consequently, after the devastation observed on Sint Maarten after Hurricane Irma, it offered the opportunity to investigate the evacuation responses of households on the island. The primary objective was to identify key variables that could effectively predict the decision-making process regarding evacuation in the context of a Small Island Developing State (SIDS) facing the imminent threat of a major hurricane.

Therefore, the research began by reviewing prior studies on hurricane evacuation to identify and select variables with the potential to be tested as predictors of evacuation. Building on this knowledge, a comprehensive field survey was conducted in the aftermath of Hurricane Irma in Sint Maarten. The primary objective was to gather relevant information that could provide insights into the observed evacuation patterns during the disaster. Subsequently, statistical analysis was performed on the collected data to assess the correlation between variables and the observed evacuation behaviors, ultimately determining the predictors of evacuation. These findings can serve as valuable inputs for a disaster risk management strategy, aimed at mitigating exposure to natural hazards and minimizing the impact of future disasters. This manuscript continues with a discussion of the results, their practical implications, and suggestions for future research directions.

2. Literature Review

The number of publications on evacuation due to disasters triggered by natural hazards is very large, with significant but often contradictory and inconclusive findings [11,13]. It remains unclear which variables are good, bad, or non-significant as predictors of evacuation, principally due to cultural and local differences as well as some hazard-specific variables. Researchers have tried to identify and categorize the critical variables that can be used as precursors of evacuation prior to a disaster. To have a comprehensive view of these variables, we have selected four well-positioned/cited review papers on evacuation behavior, covering more than 50 years of research [11–14].

The main conclusions of these reviews are presented in Appendix A. The four review papers used were as follows: [A] Baker (1991); this study presents a thorough analysis of predictors for hurricane evacuation based on information collected from 12 hurricanes from 1961 through 1989 in the USA. [B] Thompson et al. (2017) summarizes the main findings of 83 peer-reviewed articles published between 1961 and 2016 regarding evacuation from disasters triggered by natural hazards. [C] Dash and Gladwin (2007) present a review of variables affecting evacuation decision-making using three main areas—warning, risk perception, and evacuation research. Finally, [D] Huang et al. (2016) present a statistical meta-analysis that includes 49 studies on hurricane evacuation from 1991 to 2014.

From our review (of reviews), it can be concluded that there is no consensus on which elements are good or bad predictors of evacuation, which can be partially explained due to local, environmental, and cultural differences, leading to evacuation rates that will vary from place to place under the same hazard, and will vary in time; this results in different hazards in the same location [11]. It is important to mention that most of the cited studies have been performed in the continental and USA territories [12], hence the lack of understanding of predictors in other areas is more significant. In addition, to the best of our knowledge, this is the first research focused on evacuation behavior in SIDS.

Despite the lack of agreement on predictors, some conclusions can be extracted from the summary of the studies in Appendix A. Risk perception is the most accepted predictor of evacuation from a threat zone with robust and positive correlations reported continuously across studies. In addition, other widely accepted factors influencing protective behavior towards evacuation are living in flood-prone zones, having evacuated under previous evacuation orders, having experienced losses in the past (injuries, loss of life, and loss of infrastructure), and clear and direct communication of the evacuation order. Demographic variables have been extensively used to describe evacuation behavior in the past, but there has not been consistency in their global usability as predictors has been found, yet only applied to some specific cases.

3. Materials and Methods

3.1. Case Study

Saint Maarten is located in the north-east of the Caribbean Sea and is part of the Leeward Islands. The island is divided into two territories (Figure 1), the north part being an overseas collectivite of France called Saint-Martin, and the south part of the island being a constituent country of the Kingdom of the Netherlands with an area of 34 km^2 [15]. This research concerns only the Dutch part of the island, with an estimated official population of 40,535 inhabitants in 2017 [16] and an estimated undocumented population of 10,000 inhabitants when Hurricane Irma struck in 2017 [17].

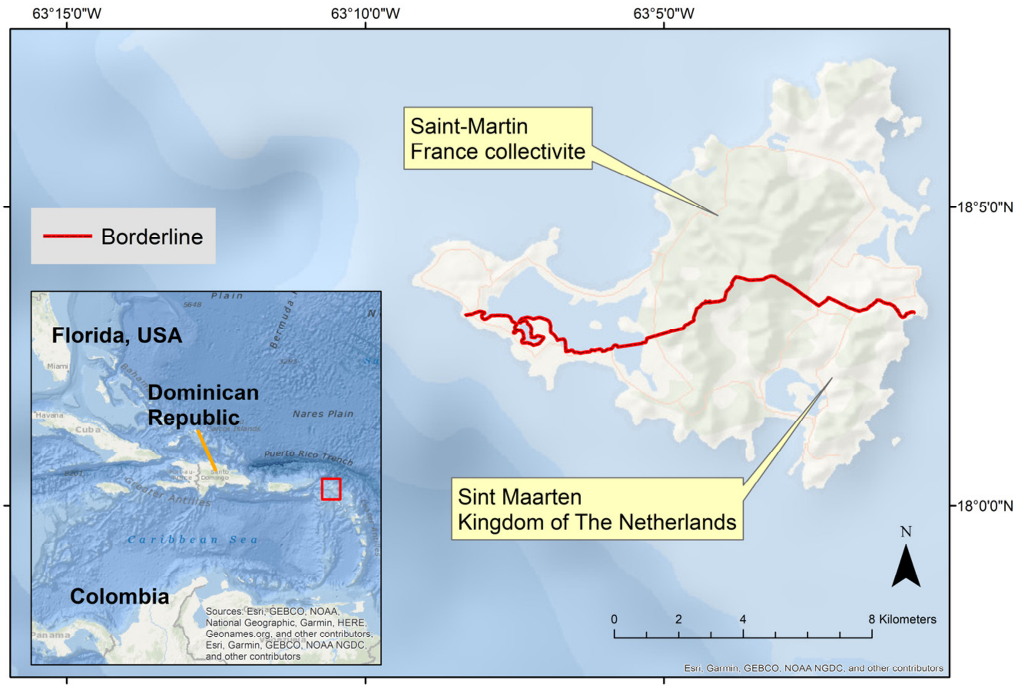

Figure 1. Location of Sint Maarten in the Caribbean Sea. On the bottom left side, the general location of the island in relation to the Caribbean Sea, the red rectangle shows the location of Sint Maarten. The study was conducted in the south part of the island (borderline in red) (own production).

The location of the island in the Atlantic Hurricane belt, makes it very susceptible to recurrent hurricane threats, bringing with them the associated wind damage, flooding, storm surges, and landslides. Since records began, 20 major hurricanes have hit the island; the most catastrophic ones include Hurricane Donna in 1960, Hurricane Luis in 1995, and more recently Hurricane Irma in 2017 [18]. Hurricane Irma, a Category 5 hurricane, made landfall on Sint Maarten on 6 September 2017 with maximum recorded winds of 295 km/h and a minimum pressure of 914 mb. At the time, it was considered the most powerful hurricane on record in the open Atlantic region [8], causing damage of more than 1 billion USD and officially killing 11 people on the whole island.

3.2. Research Design

The risk analysis and evacuation behavior on Sint Maarten is based on a field data collection and a survey campaign we performed in the aftermath of Hurricane Irma in four weeks between February and March of 2018. A mixed-mode survey was employed—a combination of face-to-face with a complimentary web survey. Survey results for a total of 255 households were obtained, corresponding to a response rate of 82.6% with a margin of error of 6.07%, using a confidence interval of 95%. The conceptual design of the survey, which includes the survey template, data preparation, sample size, collection mode, and random household selection, the field implementation and the statistical significance, as well as some preliminary results were presented and extensively explained in a previously published work by the team [19].

The work was intended to collect data concerning socio-economic vulnerability and risk to disasters triggered by natural hazards. It included components on the actual evacuation behavior during Hurricane Irma. The collected information was divided into four categories: (i) household and demographic parameters, (ii) information, awareness, and experience with hurricanes and storms, (iii) evacuation behavior, and (iv) risk perception.

3.3. Predictors to Be Analyzed

Based on the literature review, the fieldwork and survey, and the results of a socio-economic vulnerability analysis previously completed by the research team [17], we have selected a set of parameters to be tested for significance and correlation with observed evacuation behavior on Sint Maarten during Hurricane Irma. We classified the potential factors affecting evacuation decision-making behavior into six groups: demographic, socio-economic, housing, information, place, and storm characteristics, and applied variables associated with the vulnerability index computed for the island.

As shown in Table 1, the groups are composed of 20 variables and 76 categories to be tested as predictors. To have a clear interpretation of what a group in this analysis represents, it is better to first understand the category column [3], followed by the Variable [column 2], and finally the group [column 1].

Table 1. Variables and categories to be analyzed as predictors of evacuation, the number of respondents, and expected contribution towards evacuation.

[1]	[2]	[3]	[4]	[5]
Group	**Variable/Predictor**	**Category**	**Contribution**	**Respondents (%) N = 255.**
Demographic characteristics	Gender	Female Male	(+) (−)	140 (54.9%) 115 (45.1%)
	Age	18–30 31–40 41–55 56–65 >65 No Answer	(−) (+) (+) (−) (−) 	26 (10.2%) 40 (15.7%) 84 (32.9%) 32 (12.5%) 31 (12.2%) 42 (16.5%)
	Car ownership	Yes No	(+) (−)	194 (76.1%) 61 (23.9%)
	Household size	1–2 3–4 >=5	(−) (+) (+)	86 (33.7%) 107 (42%) 62 (24.3%)
Socio-economic characteristics	Homeownership	Yes (owner) No (tenant)	(−) (+)	119 (46.7%) 136 (53.3%)
	Job status	Working. Fixed location Working. Changing location Retired Unemployed No Answer	(+) (−) (−) (−) 	123 (49.4%) 51 (20.5%) 36 (14.5%) 39 (15.7%) 6 (2.4%)
Housing characteristics	House construction material—walls	Bricks Concrete Wood	(+) (−) (+)	22 (8.6%) 198 (77.6%) 35 (13.7%)
	House construction material—roof	Concrete Metal sheets Other	(−) (+) (+)	63 (24.7%) 176 (69.0%) 6 (6.3%)
	Insurance for disasters	Yes No Does not know	(+) (−) (−)	68 (26.8%) 121 (47.6%) 65 (25.6%)
	Property damage due to Hurricane Irma	0–25% 26–50% 51–75% 76–100%	(−) (−) (+) (+)	154 (60.4%) 50 (19.6%) 20 (7.8%) 31 (12.2%)
Information	Quality of message content. If a more direct and precise message is received, evacuation orders will be followed more	Strongly disagree Disagree Agree Strongly agree Other	(−) (−) (+) (+) (−)	70 (27.5%) 36 (14.1%) 78 (30.6%) 55 (21.6%) 16 (6.3%)

Table 1. *Cont.*

[1]	[2]	[3]	[4]	[5]
Group	**Variable/Predictor**	**Category**	**Contribution**	**Respondents (%) N = 255.**
Place, geographical, and storm characteristics	Length of residence.Number of years living on Sint Maarten	0–10 11–20 21–30 31–40 More than 41 No answer	(+) (+) (−) (−) (−)	39 (15.3%) 59 (23.1%) 55 (21.6%) 53 (20.8%) 45 (17.6%) 4 (1.6%)
	Hazard awareness. Number of days aware of Hurricane Irma	0–3 4–7 8–14 More than 14 No answer	(−) (+) (+) (−)	58 (22.7%) 138 (54.1%) 49 (19.2%) 8 (3.1%) 2 (0.8%)
	Perception of living in a flood-prone area	Yes No No answer	(+) (−)	21 (8.2%) 227 (89.0%) 7 (2.7%)
	Previous hurricane experience	0 1–2 3–4 5–6 More than 6	(−) (−) (+) (+) (−)	0 (0.0%) 52 (20.4%) 71 (27.8%) 47 (18.4%) 85 (33.3%)
Place, geographical, and storm characteristics	Level of worry. Frequency of checking the storm information	Once or less a day Several times a day Every couple of hours Throughout the whole day	(−) (+) (+) (+)	9 (3.6%) 26 (10.4%) 45 (18.1%) 169 (67.9%)
	Number of storeys	1 Two or more	(+) (−)	143 (56.1%) 112 (43.9%)
Vulnerability index components	Risk perception	Low Medium High Very high	(−) (−) (+) (+)	75 (29.4%) 114 (44.7%) 49 (19.2%) 17 (6.7%)
	Government performance perception	Low Medium High Very high	(−) (−) (+) (+)	108 (42.4%) 47 (18.4%) 91 (35.7%) 9 (3.5%)
	Vulnerability index	Very low Low Medium High Very high	(−) (−) (−) (+) (+)	23 (9.0%) 44 (17.3%) 44 (17.3%) 85 (33.3%) 59 (23.1%)
Evacuation behavior	Actual evacuation during Hurricane Irma	Yes = 1 No = 0	Dependent variable	80 (31.4%) 175 (68.6%)

The hypothesis to be tested using the expected contribution towards promoting (+) or reducing (−) evacuation is also presented in the table. The last column shows the frequency of the respondents' answers.

3.4. Model Analysis

In order to evaluate the relationship between the actual evacuation behavior of Sint Maarten residents and the different factors or predictors, we have conducted a Multiple Correspondence Analysis (MCA). MCA is a well-known mathematical method mostly used to analyze data obtained through surveys; it is used to identify the associations and relationships between variable and categories [20]. The MCA analysis we conducted was based on principal components as the extraction method; a scree plot analysis in combination with eigenvalues allows us to determine the number of dimensions to consider in the analysis, which for this study will be limited to the first two dimensions.

The MCA results enables the six groups in which the predictors were grouped (Table 1—column (1)) to be plotted in the first two dimensions in a biplot; this is used to evaluate if the groups are conceptually distinct constructs and can be analyzed separately. It is expected that groups that are different will appear relatively separated in the biplot. The next step was to test for correlation between the variables (Table 1—column (2)) to identify the degree of relationship between the variables and identify possible redundant variables, as well as to identify those more correlated to evacuation. Here, correlations above 0.7 are considered strong and should be removed before further analysis as possible explanatory variables, correlations around 0.5 are considered moderate relationships, and around 0.3 are considered weak relationships between variables. Once the groups and variables were proved to be independent, we used the results from the MCA analysis to evaluate whether or not each category contributes positively, negatively, or has no statistical significance according to our hypothesis presented in Table 1—column (4).

The next step in the analysis was to identify which variables are more influential (or not) as predictors of the evacuation behavior observed during Hurricane Irma. First, we conducted a χ^2 test to evaluate the relationship between the dependent variable evacuation, with all the other explanatory variables or predictors presented in Table 1—column (2). The results of this test are in the form of statistical significance for those variables that have a stronger relationship with the actual evacuation behavior, and also serves to evaluate the hypothesized effect, positive or negative, on evacuation behavior.

The outputs of both the MCA analysis and the correlation matrix allow us to determine the most significant predictors of evacuation for Sint Maarten. Using different combinations of the significant predictors, we developed binomial logistic regression models to simulate the evacuation response.

4. Results

The results of the MCA analysis of the six groups in which variables were categorized are presented in Figure 2. The distance observed between the different groups in the first two dimensions shows that all the groups can be considered conceptually distinct constructs. The validity of the use of the six groups is further supported by the correlation analysis, as presented in Table 2. The highest correlation among the scales was found to be moderate, with a correlation of 0.45 between the variables home insurance against disasters and homeownership, followed by vulnerability index and risk perception with a correlation of 0.41. No other set of variables has vulnerability greater than 0.40. Given the values of correlation obtained, the results suggest that all the variables in the analysis are distinct; hence, we can use the complete set of variables and categories in the MCA analysis to evaluate whether or not they can be used as an indicator of the actual evacuation behavior on Sint Maarten.

From the correlation matrix, there also seem to be some weak correlations involving some of the other variables. Gender and age appear somehow to be correlated to job status on Sint Maarten, with correlation $R = 0.26$ and 0.39, respectively. Age and length of residence ($R = 0.34$), and the number of house storeys ($R = 0.31$) influence to some degree the decision whether or not to take out home insurance. Property damage has a correlation with the material of the walls ($R = 0.35$). The correlation matrix also provides signs of possible predictors of evacuation; the most correlated variables are property damage ($R = 0.31$), the materials of the walls (0.28), the quality of information ($R = 0.21$), the number of house storeys ($R = 0.21$), and the insurance ($R = 0.21$).

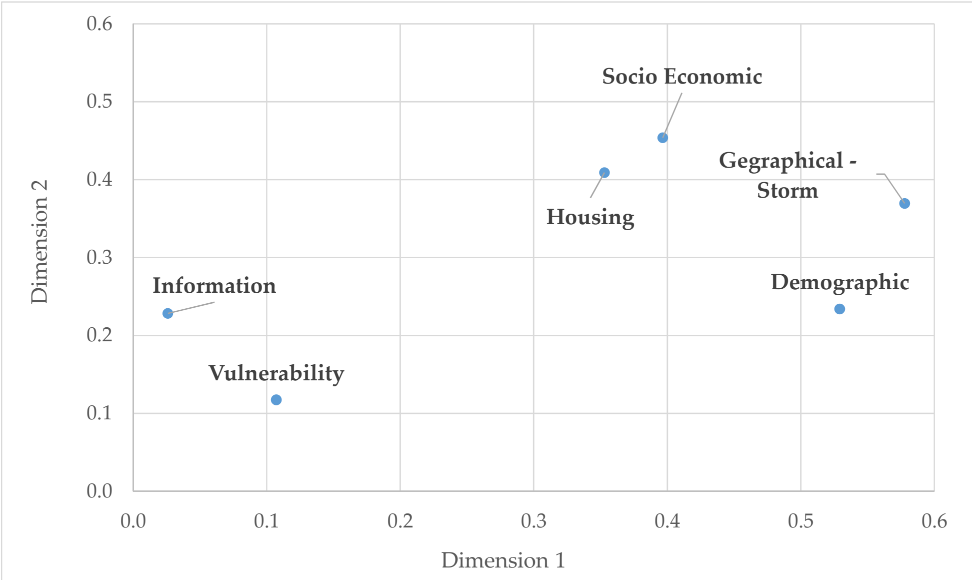

Figure 2. Group representation in the first two dimensions of the MCA analysis. **Group** (variables): **Demographic** (Gender, Age, Car ownership, Household size). **Socio-economic** (Homeownership, Job status). **Housing** (Construction materials for roofs and walls, Ownership of insurance, property damage. **Information** (Quality of warning messages). **Geographical–Storm** (Number of years living in Sint Maarten, Number of house storeys, Hazard awareness, Flood prone areas, Hurricane experience, level of worry). **Vulnerability** (Risk and government performance perception, vulnerability index).

Table 2. Correlation matrix between variables.

#	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1	Gender	1.00																				
2	Age	0.15	1.00																			
3	Car ownership	0.08	0.28	1.00																		
4	Household size	0.15	0.23	0.20	1.00																	
5	Homeownership	0.01	0.24	0.16	0.19	1.00																
6	Job status	0.26	0.39	0.18	0.12	0.20	1.00															
7	House construction—walls	0.09	0.21	0.28	0.14	0.14	0.11	1.00														
8	House construction material—roof	0.03	0.11	0.13	0.14	0.18	0.14	0.21	1.00													
9	Property damage	0.12	0.11	0.21	0.07	0.13	0.13	0.35	0.21	1.00												
10	Home insurance	0.13	0.34	0.22	0.09	0.45	0.20	0.21	0.08	0.24	1.00											
11	Public information	0.10	0.14	0.14	0.09	0.19	0.15	0.14	0.16	0.14	0.20	1.00										
12	Length of residence	0.12	0.34	0.15	0.10	0.34	0.19	0.18	0.18	0.11	0.34	0.16	1.00									
13	Flood-prone area	0.07	0.12	0.01	0.07	0.11	0.08	0.01	0.03	0.15	0.15	0.15	0.09	1.00								
14	Number of house storeys	0.01	0.31	0.20	0.02	0.04	0.17	0.22	0.03	0.20	0.31	0.17	0.28	0.05	1.00							
15	Previous experience	0.03	0.24	0.11	0.04	0.26	0.16	0.11	0.14	0.12	0.14	0.09	0.28	0.05	0.14	1.00						
16	Concern level	0.08	0.12	0.16	0.15	0.18	0.13	0.11	0.15	0.11	0.11	0.15	0.11	0.22	0.15	0.10	1.00					
17	Hazard awareness	0.11	0.08	0.07	0.15	0.13	0.10	0.07	0.11	0.12	0.12	0.12	0.12	0.13	0.10	0.12	0.15	1.00				
18	Risk perception	0.13	0.15	0.05	0.12	0.13	0.14	0.12	0.10	0.12	0.13	0.10	0.16	0.06	0.15	0.10	0.10	0.15	1.00			
19	Government performance	0.08	0.17	0.06	0.12	0.12	0.09	0.11	0.10	0.13	0.10	0.07	0.16	0.19	0.08	0.07	0.09	0.10	0.24	1.00		
20	Vulnerability index	0.11	0.17	0.10	0.16	0.07	0.18	0.14	0.21	0.13	0.17	0.14	0.16	0.08	0.13	0.12	0.12	0.14	0.41	0.34	1.00	
21	Evacuation decision	0.14	0.07	0.16	0.10	0.16	0.08	0.28	0.14	0.31	0.21	0.21	0.04	0.06	0.21	0.14	0.06	0.05	0.10	0.08	0.18	1.00

The statistical test we run for significance on the categories to evaluate our hypothesis of contribution towards positive or negative evacuation behavior is presented in Table 3. From the initial 76 categories we tested, only 18 categories were found to be significant to a level of $p < 0.05$. All the six groups are represented in the selection of significant categories, but only 11 variables from the initial 20.

Table 3. Variables and categories found to be statistically significant as predictors of evacuation. The expected and actual contribution towards evacuation is presented. The categories in bold had a different contribution to the one initially hypothesized.

Group	Variable/Predictor	Category	Expect to Contribute	Actual Contribution (*)
Demographic characteristics	Gender	Female Male	(+) (−)	(+)/(c) (−)/(c)
	Car ownership	**Yes** **No**	**(+)** **(−)**	**(−)**/(c) **(+)**/(c)
Socio-economic characteristics	Homeownership	Yes (owner) No (tenant)	(−) (+)	(−)/(c) (+)/(c)
Housing characteristics	House construction material—walls	Concrete Wood	(−) (+)	(−)/(c) (+)/(a)
	House construction material—roof	Concrete	(−)	(−)/(c)
	Insurance for disasters	**Yes** **No**	**(+)** **(−)**	**(−)**/(b) **(+)**/(b)
	Property damage due to Hurricane Irma	0–25% 76–100%	(−) (+)	(−)/(a) (+)/(a)
Information characteristics	Quality of message content. If a more direct and precise message is received, evacuation orders will be followed more	Strongly disagree	(−)	(−)/(b)
Place, geographical and storm characteristics	Perception of living in flood-prone areas	No	(−)	(−)/(c)
	Number of house storeys	1 Two or more	(+) (−)	(+)/(a) (−)/(a)
Vulnerability index components	Vulnerability index	Very low	(−)	(−)/(b)

Note(s): (*) Significant at: (a) $p < 0.001$, (b) $p < 0.01$, (c) $p < 0.05$.

From the categories' analysis, it can be inferred that households on Sint Maarten that have reported evacuating during Hurricane Irma share a high frequency for variables such as the following: high percentage of damage to their houses, the house is normally a one-storey building built with wooden walls, not having a car, and not having home insurance, they generally rent the house (tenants), and most correspond to women. In contrast, those households that did not evacuate during Irma are normally men, who consider their houses are not located in a flood-prone area, their houses suffer low damage (0–25%), and are built with concrete walls and roof, and they are normally the owners of the house. They have insurance for disasters triggered by natural hazards, and there is a high frequency of having two or more storeys; in addition, they live in areas with a very low vulnerability index.

Regarding the hypothesized effects of the categories that were found to be statistically significant, almost all the categories had the hypothesized effect on evacuation behavior, with the two exceptions of car ownership and insurance for disasters. It was initially expected that households that have insurance and own a car would favor evacuation but instead the opposite was found; these two elements were found to have a negative effect on evacuation on Sint Maarten.

The quality of the content regarding information had one category with a negatively associated correlation effect on evacuation, meaning that those individuals that strongly disagree with the statement asked tended to be less likely to evacuate on Sint Maarten. Regarding those categories in the group of place and storm characteristics, we found, as expected, that one-storey building households tend to be more likely to evacuate in contrast to those living in a house with two or more storeys. Similarly, perception of living in an area not prone to floods also had a negative correlation with evacuation. From the vulnerability group, only those households with a very low vulnerability index were found to have a negative effect on evacuation, as initially hypothesized.

From the variables with statistical significance towards contributing to the decision by a household to evacuate, property damage is the most significant variable, followed by the material of the walls, and third in importance is the perception of living in a flood-prone area. The number of house storeys was also found to be significant as well as the quality of the information received during an emergency. In addition, gender in combination with having a car, having insurance, and being the owner of the house seems to play a part in the decision whether to evacuate or to stay.

As the next step, we ran a binomial logistic regression model on the variables (Table 1—column (2)). Regressing the evacuation decision against all the other variables in the model (see Table 4, Model 1) showed that gender, homeownership, and the number of house storeys had a negative effect on the observed evacuation behavior. In contrast, property damage, quality of the information, and the vulnerability index all showed a positive effect. Similarly, Model 2 in Table 4 presents the re-computed regression results after removing the non-significant variables from Model 1. The changes in the regression coefficients of Model M2 were minimal and kept the associated positive or negative effect observed in M1. The errors in predictions related to Model M2 were minimal according to the residual deviance. M2 shows a superior balance between its ability to fit the data set and its ability to avoid over-fitting the model measured by the AIC score.

Table 4. Binomial logistic regression model. Prediction of the evacuation decision. Model 1 is built using all the variables. Model 2 is built using the statistically significant parameters of Model 1. The variables in bold were found to be statistically significant at 'a' $p < 0.001$, 'b' $p < 0.01$, 'c' $p < 0.05$, 'd' $p < 0.1$.

Variable	Model 1 (M1)			Model 2 (M2)		
	β	SE (β)	Odd Ratio	β	SE (β)	Odd Ratio
Gender	**−0.683** [c]	0.318	0.505	**−0.6623** [c]	0.305	0.516
Age	0.176	0.183	1.192			
Car ownership	0.028	0.380	1.028			
Household size	−0.111	0.228	0.895			
Homeownership	**−0.658** [d]	0.369	0.518	**−0.6769** [c]	0.308	0.508
Job status	−0.051	0.145	0.950			
House construction material—walls	0.036	0.368	1.037			
House construction material—roof	0.388	0.321	1.473			
Property damage	**0.449** [b]	0.158	1.566	**0.4831** [a]	0.138	1.621
Insurance for disasters	−0.170	0.242	0.844			
Information. Quality of message content	**0.259** [c]	0.130	1.296	**0.2376** [c]	0.121	1.268
Length of residence	0.008	0.158	1.008			
Perception of living in flood-prone area	−0.002	0.560	0.998			
Number of house storeys	**−0.694** [c]	0.352	0.500	**−0.7494** [c]	0.316	0.473
Previous hurricane experience	−0.197	0.157	0.822			
Concern level	−0.043	0.185	0.958			
Hazard awareness	0.033	0.217	1.034			
Risk perception	−0.121	0.193	0.886			
Government performance perception	0.120	0.171	1.127			
Vulnerability index	**0.266** [c]	0.135	1.304	**0.2429** [d]	0.125	1.275
Intercept	−0.316	2.211	0.729	−0.2126	1.041	0.808
Null deviance	317.25 on 254 df			317.25 on 254 df		
Residual deviance	264.76 on 234 df			270.87 on 248 df		
AIC	306.76			284.87		

Furthermore, to gain an understanding of the predictors of actual evacuation, we computed the logistic regression models for the categories (Table 1—column (3)). We developed two binomial logistic regression models. We built the models using a random sample of 80% of the dataset and leaving the remaining 20% of the data for validation purposes.

First, we ran a logistic model using the categories listed in Table 3; these are the categories with statistical significance in the chi-square test. The result of this model is presented in Table 5—Logit-i. In this logit model, male gender, concrete walls, living in a multi-storey building, and strongly disagreeing in the information content component all have a predicted negative effect on evacuation behavior. On the other hand, being a tenant, suffering damage between 76–100% during a storm, and not having home insurance for disasters triggered by natural hazards all have a positive effect leading to evacuation. The second logit model (Logit-ii in Table 5) was built with the variables in (M2) in Table 4. The Logit-ii results show that strongly disagreeing with information has the most substantial negative effect, followed by multi-storey buildings and male gender. In contrast, property damage (75–100%) was found to have the greatest observed positive effect on evacuation, followed by the category tenant in the house ownership variable.

Table 5. Prediction of evacuation decision. Binomial logistic regression models.

Variable. Category		Logit-i			Logit-ii	
	β	SE (β)	Odd Ratio	β	SE (β)	Odd Ratio
Gender. Male	-0.769 [c]	0.337	0.464	-0.566 [d]	0.313	0.568
Car ownership. Yes	0.194	0.393	1.215			
Homeownership. Tenant	0.976 [b]	0.370	2.654	0.707 [c]	0.317	2.027
House construction material—walls. Concrete	-1.025 [d]	0.540	0.359			
House construction material—walls. Wood	0.225	0.692	0.798			
Property damage. Damage 26–50%	-0.292	0.411	1.340	-0.297	0.393	1.346
Property damage. Damage 51–75%	0.003	0.593	1.003	0.490	0.542	1.633
Property damage. Damage 76–100%	1.074 [c]	0.537	2.926	1.584 [a]	0.462	4.874
Insurance for disasters. No	0.834 [d]	0.429	2.302			
Insurance for disasters. Yes	-0.214	0.512	1.239			
Information. Quality of Content. Disagree	-0.565	0.527	0.568	-0.481	0.511	0.618
Information. Quality of content. Other	-0.488	0.695	0.614	-0.376	0.643	0.687
Information. Quality of content. Agree	0.026	0.429	0.974	0.049	0.404	0.952
Information. Quality of content. Strongly disagree	-0.961 [c]	0.441	0.383	-1.002 [c]	0.426	0.367
Perception of living in flood-prone area. Yes	0.121	0.565	1.128			
Number of house storeys. Two or more	-0.603 [d]	0.36	0.547	-0.776 [c]	0.327	0.460
Vulnerability index. Low				-0.113	0.462	0.893
Vulnerability index. Medium				-0.239	0.459	0.787
Vulnerability index. Very high				0.406	0.399	1.501
Vulnerability index. Very low				-1.187	0.804	0.305
Intercept	-0.553	0.800	0.575	-0.596	0.420	0.551
Null deviance		317.25 on 254 df			317.25 on 254 df	
Residual deviance		249.05 on 237 df			264.94 on 240 df	
AIC		285.05			294.94	

Note(s): Significant at: 'a' $p < 0.001$, 'b' $p < 0.01$, 'c' $p < 0.05$, 'd' $p < 0.1$.

Concerning the values of the null deviance, it is relatively higher than the degrees of freedom (df), meaning that it makes sense to use more than a single parameter (intercept) for fitting the two models. In terms of the residual deviance for the two models, this is relatively low and close to the degrees of freedom, implying an appropriate and well-fitting model. In addition, the values of the Akaike Information Criterion (AIC) allow us to compare the level of complexity between the models. The model with the lower AIC score is expected to have a better balance between its ability to fit the data set and its ability to avoid over-fitting the model. Logit-i is the best of the models in terms of the AIC coefficient, but the AIC values for all the models are relatively similar, which means there is not a clearly superior model.

In addition, to evaluate the performance of the two logistic models, we estimate the prediction accuracy and the prediction errors. The data were split randomly into training and validation data sets, using the rule of thumb 80–20% of the data, respectively. The predictive power of the logistic models was then assessed by comparing the predicted outcome values against the known outcome values. Different metrics on model performance evaluation are presented in Table 6.

Table 6. Performance evaluation of the binomial regression logistic models.

Variable	Logit Model	
	Logit-i	**Logit-ii**
Accuracy [%]	74.5	76.5
95% CI	60.4–85.7	62.5–87.2
Sensitivity [%]	52.6	52.6
Specificity [%]	87.5	90.6
ROC curve [AUC]	0.822	0.825

The first value to evaluate the model performance is the overall classification accuracy; this value for the three models is relatively high with accuracies above 70%, with Logit-ii yielding the best results, correctly predicting the individual outcome in 76.5% of the cases and with a confidence interval (95% CI) between 62.5% and 87.2%.

Model performance was also measured using the values of sensitivity and specificity. Sensitivity in the model assessment refers to the number of times the model was able to correctly predict the cases where a household performs an evacuation. In contrast, specificity refers to the number of times the model was able to correctly predict those households that did not evacuate. The importance of sensitivity and specificity parameters depends on the context; for evacuation processes, it is more important to have minimal wrong positive predictions (high specificity); this is forecasting that a household would evacuate, but in reality, it does not. Minimal wrong positive predictions translate into having a more precise picture of how many households decide to stay in their houses, potentially requiring assistance during or in the direct aftermath of a disaster. Specificity for all the models is above 80%, and the Logit-ii model rate is higher than for Logit-I with 90.6%. Regarding the sensitivity of the regression models, it is the same in the two models.

Finally, the Area Under the Curve (AUC) from a ROC curve analysis summarizes the overall performance of the prediction. The AUC metric varies between 0.50 (random prediction) and 1.00 (perfect prediction). Values above 0.80 are an indication of a good predictor. In our regression models, the models Logit-ii is slightly better predictor than Logit-i.

The performance evaluation suggests that the model that better predicts the evacuation behavior on Sint Maarten is the Logit-ii model. The model is composed of six variables/predictors: gender, homeownership, percentage of property damage, quality of the information, number of house storeys, and the vulnerability index. The general equation from a logistic model is presented in Equation (1).

$$\log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \beta_k x_{ik} \tag{1}$$

where:

p = Probability of evacuation
β_0 = intercept
β_1 = Beta coefficient for parameter 1
x_{i1} = Value of parameter 1
β_k = Beta coefficient for parameter k

x_{ik} = Value of parameter k

The function depicted in Equation (1) corresponds to a logarithmic function, hence the value of p will always be between 0 and 1. To assess whether the value of p indicates a household evacuating or not Equations (2) and (3) are used.

$$From\ Equation\ (1).\quad If\ p \geq 0.5\ then\ Evacuation = Yes \tag{2}$$

$$From\ Equation\ (1).\quad If\ p < 0.5\ then\ Evacuation = No \tag{3}$$

5. Discussion

Evacuation on Sint Maarten needs to be seen and understood in the context of a small island developing state (SIDS). Evacuation processes are challenging everywhere, but the context of a SIDS makes it particularly so in several ways. Firstly, a SIDS is strongly associated with the low socio-economic status of its inhabitants [21], which makes it almost impossible for a significant part of the population to flee the island no matter the severity of the hazard that is forecasted. Secondly, considering the relatively small size of the islands compared to the magnitude of a major hurricane, evacuees, irrespective of their location on the island, cannot entirely evade exposure to the hazard, which may substantially impact their decision not to evacuate. Thirdly, in the case of Sint Maarten, a notable population of around 10,000 consists of undocumented immigrants [17]. These individuals tend to avoid official shelters for fear of deportation, while limited social connections within the island restrict their options for seeking safer grounds during hazardous events such as floods or hurricanes [22].

The results of this study confirm the close relationship between evacuation decisions on Sint Maarten and various demographic, socio-economic, housing, information, place, storm characteristics, and vulnerability factors. Although there are not as many variables that significantly predict evacuation as those that were tested (11 out of 20), noteworthy findings can be drawn from the results.

Demographic characteristics have been reported as non-conclusive across multiple studies. However, for Sint Maarten, it was found that male gender is a predictor not to evacuate. Women have been reported in other studies to comply better with evacuation instructions and to have a better risk assessment [13,23,24]. Furthermore, during the fieldwork, one of the reasons given for not evacuating included that they wanted to protect their homes from looting or from the storm itself. We found that some households leave at least one person behind, usually the father, to protect the property. This situation was reported to happen even if the rest of the household evacuates, behavior that is contrary to prior findings that indicate that households tend to evacuate (or to stay) as a unit [25]. We identify that looting is a big concern among the population of Sint Maarten, especially after Hurricane Irma, where shops and houses were heavily looted. Disaster risk managers on the island should be concerned about this perception because it is affecting people's willingness to evacuate. Extra security in areas at high risk of looting should be guaranteed and communicated in time to promote timely evacuation in those areas.

We found that car ownership is a significant variable of a household's behavior towards evacuation, which is contrary to the hypothesized effect; it was expected that households with a vehicle would be more likely to evacuate [26,27]. However, having a car on Sint Maarten is associated with those households that did not evacuate and that, in contrast, not having a car is correlated with households that did evacuate during Hurricane Irma; a similar counterintuitive result was found by Lazo et al. (2015) [28]. Not having a car promoting evacuation might be explained in two ways. First, households that do not have a vehicle may feel the need to evacuate early as they do not want to be trapped in the middle of the hurricane in their houses. Second, public transport may be suspended during a forecasted hurricane, making it difficult to evacuate when the hurricane is approaching. On the other hand, having a car may create a feeling of non-urgency to evacuate, as they may (falsely) think they can evacuate whenever they want. Another explanation could be that the few roads available on the island have limited capacity, resulting in long traffic jams even in normal traffic conditions. Households may prefer to avoid driving during an evacuation for the discomfort associated with driving during an evacuation or to avoid being trapped in a traffic jam when the hurricane strikes [28].

Our findings regarding homeownership indicate that tenants have a higher tendency to evacuate than homeowners, which corresponds to previous research [28,29]. Owners may feel the "need" or "desire" to stay at home to protect the house during the storm or from looters [10,11,30]. In addition, owners tend to do more regular maintenance on their house and hence feel more protected than in a public shelter or other destination. In contrast, tenants may not need the feel to properly maintain the household to a condition that withstands a hurricane force as they feel it is the owner's responsibility [19]. This helps explaining why tenants on Sint Maarten evacuate more often. Furthermore, owners may not evacuate to avoid the discomfort and environment of public shelters [11], in contrast to some tenants who are low-income evacuees or undocumented immigrants for whom public shelters may be the main and sometimes the only place to evacuate to [31].

Household construction material was found to be one of the strongest co-founders of evacuation behavior on Sint Maarten. Households built with stronger materials (i.e., concrete walls and roof) tend to be less likely to evacuate than those living in houses built with weaker materials (i.e., wood). Perception of having a strong house was already reported in the literature to prevent people from evacuating. It has been reported that when households feel unsafe at their location and perceive their house as vulnerable to wind damage during a storm, this tends to increase their tendency to evacuate, and those who feel safe tend to stay [11,28,32].

Property damage for Sint Maarten was the predictor with the strongest statistical significance; it was found that those houses suffering the most (76–100% damage) were also more likely to evacuate. In contrast, households with lower levels of damage (0–25% damage) were found to be those less likely to evacuate. The expectation of damage or damage suffered in the past has been consistently reported as a good predictor of evacuation [11,33–35]. When individuals feel they or their relatives are at risk of death or injury, or that their house could face serious damage, they are more likely to evacuate.

Multi-storey residences on Sint Maarten tend to be less likely to evacuate than single-storey houses. It has been previously reported that multi-storey buildings have lower evacuation rates [36]. Lower evacuation rates can be explained due to the possibility to look for higher grounds in the case of a flood event, or the possibility to protect valuables from potential floods. In addition, multi-storey buildings on the island are normally built with concrete, which was explained above as a predictor of no-evacuation behavior.

The results of this research also suggest that those households on Sint Maarten perceiving they are located in a flood- or storm surge-prone area are more likely to evacuate than those that reported they do not live in those areas. Houses having only a ground floor or located in flood-prone risk areas such as lowlands and the coastline are more vulnerable to flooding, property damage, and even suffering casualties in the past, which in turn is a predictor of future evacuation when a warning is received [11,24]. Furthermore, it will be necessary that emergency management officials on the island update the identification of areas prone to floods and storm surge, and perform awareness campaigns of the population at risk in these areas to prompt evacuation when needed in future evacuation scenarios.

Home insurance against disasters triggered by natural hazards was hypothesized as a precursor of evacuation, expecting that households with insurance will evacuate more as they feel they can leave the house and recover their losses through their insurance company. However, our results were contrary to this assumption, and insured households on the island tend not to evacuate. This finding can be a cofounder of homeownership, as presented in the correlation matrix (R = 0.45). Homeowners are more likely to have home insurance [14], and on Sint Maarten homeownership was already explained as a strong predictor of non-evacuation.

We also found that the quality of the information that is sent in different phases of a disaster plays a role in evacuation behavior. We found that respondents of the survey that disagree with the statement that a more direct message will lead to complying more with evacuation orders are those that tend to be less likely to evacuate, and those that agree tend to be more likely to evacuate. Information content was also found to be an important predictor of evacuation behavior in other studies [11,14,24]. Prior studies have listed actions and information distributed by public officials as amongst the most important variables affecting the public response to evacuation. In addition, households are more likely to evacuate when they understand without question that an evacuation order applies to them, hence more custom-made ways of delivering the message may result in higher evacuation rates [11,29].

The variable vulnerability was found to be statistically significant as a precursor of no evacuation for those households located in very low vulnerability index areas. Households on Sint Maarten associated with low vulnerability are normally those households with higher incomes, more education, stronger construction materials, more awareness of natural risk, and more possibilities to take immediate action to protect themselves against a natural hazard [17].

In addition, nine variables did not play any significant role in explaining evacuation intentions in the case of Sint Maarten. Variables associated with risk and vulnerability in our study were used given their strong positive effects found in prior research; these are the length of residence, hazard awareness, previous hurricane experience, level of worry, risk perception, and government performance. However, none of these variables offered a major influence on evacuation behavior on Sint Maarten. One possible reason for this is that respondents may evaluate their risk and vulnerability with a more tangible measure such as house construction materials, or actual or expected damage from hurricanes.

Reflecting on the evaluation of evacuation, further research is required to enhance the ability to predict whether individuals or groups will evacuate in the face of specific threats. For instance, there is a clear need to gain a deeper understanding of the impact of non-official sources of information on promoting or hindering evacuation, as well as explore how new technologies such as social media can contribute (or not) to achieving more effective response and evacuation measures. Moreover, future research should not only focus on identifying the characteristics or variables that contribute to individuals or groups opting for evacuation, but also attempt to understand the influence of other internal or external factors on the decision-making process.

There are two key aspect that we did not explicitly include in our analysis, and that can shed some light on future research direction: the evacuation of vulnerable population, and the use of new technologies to improve evacuation plans. In the context of evacuating vulnerable populations, various decision-making methods can be employed to enhance the effectiveness and efficiency of evacuation efforts. Evacuation models can benefit from incorporating the complexity and uncertainty associated with extreme hazards into optimization models [37], or by incorporating spatially represented flood models into evacuation plans of vulnerable population [38]. On the use of new technologies, implementing a robust weather forecasting system is a vital component of any effective disaster risk management plan and of evacuation. Ensemble flood forecasting techniques [39] and operational forecasting and monitoring systems [40], have emerged as promising approaches to enhance the prediction of potential threats, such as hurricanes and floods. By employing these techniques, it becomes possible to disseminate more timely and reliable messages regarding the potential level of hazard to the affected population. Consequently, this can lead to improved evacuation or protective behaviors.

6. Conclusions

This study explores the relationship between several variables with evacuation behavior in the context of a small island developing state (SIDS) that was devastated by a hurricane. Hence, the findings and evidence provided in this research are valuable to understand what the variables are that can be used as predictors of evacuation in such a context.

Most of the findings of this study are consistent with the hypothesized effects. In this regard, gender, homeownership, a house's construction material, property damage, quality of the evacuation information, number of house storeys, perception of living in a flood-prone area, and vulnerability index were found to be influential factors. Car ownership and home insurance for disasters were also found to be statistically significant but with contradictory effect to that expected.

We found that on Sint Maarten, people are most likely not to evacuate when a hurricane is forecast. This could be partially explained because the majority of residents do not fully rationalize the magnitude and potential consequences of a major hurricane. Several storms hit the island between the last major disaster in 1995 associated and Hurricane Irma in 2017, storms and hurricanes in which residents were relatively safe and no substantial losses were reported, creating a false sense of security, and limiting households' willingness to evacuate. In addition, an evacuee under (almost) certainty of exposure to an upcoming threat, as in the case of Sint Maarten, may feel more comfortable or safe staying in their own house. This statement is not valid if the evacuee feels (or knows) their house is not strong enough or if they perceive that they live in a flood-prone or storm surge area according to our results.

People's perception of how strong their houses are in combination with past or expected damage assessment were found to be the strongest indicators of evacuation behavior on Sint Maarten. Therefore, assessment of a household's perceptions of the structural vulnerability of their houses to disasters triggered by natural hazards will be beneficial to estimate future evacuations behaviors. This is important after Irma because we observed the ongoing reconstruction of houses across the island during the fieldwork, which may create a (false) sense of security for those houses that were rebuilt after the disaster.

If a major hurricane is forecast in the coming years, before the memory of Irma fades, the government of the island should be prepared to open public shelters with enough resources, as we forecast an increasing demand for facilities. The expected increase in number of evacuees is related with new evacuees due to the fear of a new disaster, and evacuation to hotels may decrease due to the extensive damage to the infrastructure in this sector. Further, another segment of the population will always need a place to shelter—those with low income and undocumented immigrants that generally live in high-risk areas and in homes with poor construction materials. In contrast, there is a segment of the population that will never evacuate no matter how big the threat is, as long as they feel they are safe in their own houses or feel they need to stay to protect the house or to prevent looting. The government should be ready to assist those that may need immediate relief and assistance in the case of a major disaster.

Amongst the most important predictors of evacuation on Sint Maarten is the proper distribution of warning information according to our regression models of evacuation. This is an important finding for Sint Maarten disaster risk management because amongst the predictors we found statistically significant in this study, information and some components of the vulnerability index are the only ones that may be possible to influence directly without the need of investment in expensive infrastructure at the household or island level. The message content must reflect the need to evacuate; often official orders are misunderstood as advisory and may lead to non-evacuation.

This study also has some limitations; due to the restrictions posed by the post-disaster environment in which the survey was carried out we did not ask in the survey several potential predictors of evacuation; amongst those are household income, high income increases the probability of people going to a hotel rather than to a public shelter [25,41] or, in the case of Sint Maarten, the possibility to evacuate the island before a hurricane landfall. Prior evacuation behavior has also been reported as a good predictor for future evacuation [12]. Unfortunately, we did not collect this information, and exploring its statistical significance could add another helpful predictor to our logistic regression models.

The role of faith and religious groups in the evacuation decision making would also be interesting to explore; we did not directly include such an element. Hence, no statistical significance on this can be drawn from our data, but in our data collection, it was constantly mentioned by the respondents that they just put their lives in the hands of 'God' and expect the best outcome when faced with a disaster triggered by natural hazards. These limitations offer opportunities for further research.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Principal variables affecting evacuation behavior found in previous research, extracted from [A] Baker (1991) [11], [B] Thompson et al. (2017) [12], [C] Dash and Gladwin (2007) [13], and [D] Huang et al. (2016) [14]. Positively (+): predictor of evacuation. Negatively (−): predictor of non-evacuation. Not conclusive: (+) in some studies and (−) in others. No effect: no statistical significance has been found either to promote evacuation or not.

Group	Variable/Predictor	Contribute to Evacuate	Reference	Note
Demographic characteristics	Gender	Positively	[B]–[C]	Females are more likely to follow an evacuation order.
		Not conclusive	[A]–[D]	Variable that is not typically associated with actual evacuation rates, or non-significant results have been found.
	Age	Negatively	[B]–[C]	The older segment of the population is associated with limited mobility, hence less likelihood of evacuation.
		Positively	[A]–[B]–[C]	Families with children tend to seek refuge more. Elderly residents in retirement areas have a higher tendency to evacuate (assisted).

Group	Variable/Predictor	Contribute to Evacuate	Reference	Note
		No effect	[D]	Non-significant statistical correlation is reported.
	Race/ethnicity	Positively	[B]–[C]	Whites and Caucasians were found to evacuate more than other races.
		Negatively	[B]	Blacks and Hispanics are reported to evacuate less often; it might be a co-founder of income.
		No effect	[D]	Non-significant statistical correlation is reported.
	Car ownership	Not conclusive	[A]	Variable that is not typically associated with actual evacuation rates, or non-significant results have been found.
	Disabled population	Not conclusive	[B]–[C]	Limited mobility may produce less evacuation behavior. Alternatively, due to their limited mobility, this segment of the population may start the evacuation early.
	Pets	Negatively	[B]	Households with pets have a lower tendency to evacuate than those without one. Difficulty to accommodate pets in shelters or hotels may explain this behavior.
		Not conclusive	[A]	Variable that is not typically associated with actual evacuation rates, or non-significant results have been found.
Socio-economic characteristics	Level of education	Not conclusive	[A]–[B]	Variable that is not typically associated with actual evacuation rates, or non-significant results have been found. Some studies found a high correlation, others no correlation at all.
		No effect	[D]	Non-significant statistical correlation is reported.
	Household income	Not conclusive	[B]	Some studies found a high correlation, others no correlation at all between the income of a household and actual evacuation behavior.
		Positively	[C]	Higher incomes were associated with higher evacuation rates.
		No effect	[D]	Non-significant statistical correlation is reported.
	Home ownership	Negatively	[B]–[D]	Owning a house has often been found to affect evacuation behavior. Residents feel safer at home or prefer to stay to do repairs.
		Not conclusive	[A]	Variable is not typically associated with evacuation.
	Household size	Negatively	[C]	Single families have a lower tendency to evacuate.
		Positively	[B]	Houses with children have a higher tendency to evacuate.
		No effect	[D]	Non-significant statistical correlation is reported.

Group	Variable/Predictor	Contribute to Evacuate	Reference	Note
Housing characteristics	Type of house	Positively	[A]–[B]–[D]	Those with fragile houses, such as mobile homes or boats, have a higher tendency to evacuate.
		Negatively	[A]–[B]	Perception of having a strong house may lead to low evacuation rates.
	Protection of the house	Negatively	[A]–[C]	Stay home to protect from looters or to do some repairs during the storm.
		No effect	[D]	Non-significant statistical correlation is reported.
	Property damage	Positively	[A]–[B]–[C]–[D]	The bigger the loss (past or expected), the more likely to evacuate.
Information	Government evacuation order	Positively	[A]–[B]–[C]–[D]	If a mandatory evacuation is communicated. In some cultures, obeying authority figures or being afraid of receiving a fine may lead to higher evacuation rates.
	Message content	Positively	[B]–[C]	The more specific and personalized the message, and the more urgency to evacuate, the higher the evacuation rates.
	Information from neighbors, friends, or family	Not conclusive	[A]	Social cohesion may lead to higher evacuation rate to follow or reunite with family or close friends. Neighbors of relatives not evacuating may lead to lower evacuation rates due to peer pressure.
		Positively	[B]–[C]	Peers, friends, or family members acting as a warning information source have resulted in evacuation behavior, especially in communities where the family is the center of society (i.e., Hispanic). Faith groups also have a role in disseminating evacuation orders and a higher number of evacuees.
		No effect	[D]	Non-significant statistical correlation is reported.
	False alarms, 'crying wolf' phenomenon	Negatively	[B]	Near-miss experiences lead to failure to evacuate in future warnings.
		No effect	[A]–[D]	No correlation was found between false alarms and evacuation behavior in subsequent hurricanes.
	Frequency of gathering information	No effect	[A]	No significance between evacuation and frequency of media attention, keeping a tracking chart.
	Source of information	Positively	[B]–[D]	Perceived trustworthiness of the source has been found as a good predictor of accepting an evacuation order (or advice).
		No effect	[A]	No significance between evacuation and the source of information. (i.e., official, TV, radio, friends).

Group	Variable/Predictor	Contribute to Evacuate	Reference	Note
Place, geography, and storm characteristics	Length of residence in a place	Not conclusive	[A]–[B]	Newcomers do not know about potential risks. Long-term residents have a better knowledge of the risk in their residence area.
		Negatively	[C]	Number of years in a place influences evacuation behavior; the longer the resident has lived in an area, the lower the evacuation rates.
	Hazard awareness	Positively	[C]	Being aware of living in a high-risk area increases the evacuation probability.
		No effect	[A]	Weak correlation between evacuation and belief that the storm will hit.
		Not conclusive	[D]	Actual evacuation studies have reported positive correlation and non-significant correlation.
Place, geography, and storm characteristics	High risk areas	Positively	[A]–[C]–[D]	Households located in low-lying/flood-prone areas have a higher tendency to evacuate.
	Previous disaster experience	Positively	[C]	Previous experience plays a role in evacuation behavior.
		Not conclusive	[A]–[B]–[D]	Self-reported past experiences have no predictive power of what households did in subsequent hurricanes.
	Prior evacuation behavior	Positively	[A]–[B]	People that have already evacuated under previous evacuations orders are more likely to evacuate again.
	Disaster (perceived) intensity	Positively	[A]–[B]–[C]–[D]	More intention to evacuate is found under threat of a larger or more intense disaster, such as a higher category hurricane.
	Number of storeys	Positively	[B]	Those living on ground floors have a higher tendency to evacuate in flood-prone areas.
	Risk perception	Positively	[A]–[B]–[C]–[D]	The higher the perceived risk, the higher the tendency to evacuate.
	Discomfort of evacuation	Negatively	[A]–[C]	Forecast traffic jams, shelter conditions, not having anywhere to go, or the impossibility to return home in the aftermath of the disaster.

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