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Vulnerability Assessment during Mass Evacuation: Integrated Microsimulation-Based Evacuation Modeling Approach

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Abstract

This study develops an integrated microsimulation-based evacuation model that performs a vulnerability assessment of the Halifax Peninsula, Canada during an evacuation. The proposed framework of vulnerability assessment accounts for long-term changes in neighborhood composition in relation to socio-demographic characteristics, residential locations, and vehicle ownership. The results of a large-scale urban systems model and a flood risk model are used to inform the vulnerability assessment. The urban systems model encapsulates long-term household decisions and life stage transitions in measuring social vulnerability. The flood risk model provides information on flood severity and finer network disruptions. In addition, a dynamic traffic assignment-based microsimulation model is developed to assess mobility vulnerability during an evacuation. One of the key contributions of this study is that it utilizes a Bayesian Belief Network modeling approach for vulnerability assessment, while addressing uncertainty and causal relationships between different elements of vulnerability. The results suggest that the Peninsula zones are at a relatively higher risk from a mobility point of view. A sensitivity analysis reveals that clearance time has been found to be the key determinant of the mobility vulnerability during an evacuation. “Presence of female” and “presence of seniors” are found as the two most significant contributors of social vulnerability. Several peripheral zones are at a higher risk because of their proximity to the flood source. The proposed research will help emergency professionals and engineers to develop effective evacuation plans in relation to vulnerable areas.

Mass evacuation from a disaster-prone area to shelters has the potential to prolong the evacuation procedure during an emergency. Spatial zones that are at a relatively higher risk of natural disaster impacts, evacuation difficulty, or both, can be prioritized for evacuation. This will reduce traffic demand in the network, improve overall traffic flows and the safety of all. In current practice, the vulnerability of potentially affected zones is determined based on geophysical conditions that yield seriousness of risk and the social systems which refer to variations of risk (*1*, *2*). Most studies are static in nature and perform as an independent process (*3*, *4*). However, vulnerability in disaster-prone areas is dynamic and often stems from mobility complexity, including flood flows and traffic movements. Vulnerability assessment taking an integrated approach is not well explored with respect to geophysical condition, social risk, and traffic movement; even though this type of analysis would offer a better understanding towards developing effective and efficient evacuation plans.

How quickly the population of a zone can be evacuated safely before a disaster impact is a critical aspect in emergency evacuation planning. The condition of a transportation network over the affected region, traffic flow pattern, network supply, and evacuation demand determine the complexity of an evacuation operation from a traffic management point of view. For example, a lower network capacity poses a higher risk for mass evacuation of an area. Simultaneously, meeting the transportation needs of the vulnerable population, such as the carless population group, could elevate the complexity of an evacuation operation. The main challenge in estimating evacuation risk is that observation of an evacuation event is often not feasible, particularly in coastal areas, resulting in insufficient knowledge of traffic flow patterns. Additionally, difficulties in measuring social vulnerability for coastal areas results from a lack of understanding of demographic changes and key household decisions that

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affect land use patterns. Therefore, it is necessary to develop an integrated modeling system that includes modeling elements of long-term changes, such as: residential mobility decisions, vehicle ownership, flood risks, traffic movement, and vulnerability assessment. Particularly, combining integrated urban systems models and traffic microsimulation models is advantageous as the forecasted results can be used to develop evacuation plans for any number of years to come. Thus, an integrated evacuation modeling framework is of paramount importance for a reliable estimate of vulnerability.

The objective of this study is to develop an integrated microsimulation-based evacuation model which combines: (i) an integrated urban systems model that simulates land use variations and auto ownership over the course of time, (ii) a flood risk model that predicts flood severity and flood-related network disruptions, and (iii) a dynamic traffic assignment (DTA)-based microsimulation model that provides network supply constraints. The integrated urban systems model simulates long-term changes in demographic characteristics, particularly residential location choices and vehicle transaction decisions within a long-term simulator. The results of the long-term simulator can then be used to determine social vulnerability. The flood risk model informs flood severity and network disruptions for developing evacuation scenarios. Evacuation scenarios are simulated within the microsimulation model to measure mobility risk during an emergency. The proposed integrated modeling framework is empirically tested for assessing the vulnerability of areas identified as traffic analysis zones (TAZs) on the Halifax Peninsula, Canada. For the vulnerability assessment model, this study proposes a novel approach utilizing a Bayesian Belief Network (BBN) that uses information obtained from the integrated urban systems model, flood risk model, and traffic microsimulation model. It uses an Analytical Hierarchy Process (AHP) to determine the weighting factors of the vulnerability variables of interests. The vulnerability assessment model informs different evacuation planning scenarios for an empirical application.

Literature Review

The vulnerability of an area is measured by the extent of potential impacts and the degree of exposure, susceptibility, and resilience (*5*, *6*). Several methods are proposed in existing literature to estimate vulnerability in relation to natural disasters, socio-economic diversity, or both. Fernandez and Lutz applied a multi-criteria decision-making analysis to develop a flood hazard zoning system for an urban area (*5*). Their study modeled disaster impacts over an area and addressed the natural system component of vulnerability assessment. Rygel et al. explored how various groups of people are affected differently by a natural disaster based on socio-demographic heterogeneity (*7*). They assessed the vulnerability as a measure of resistance capacity of that area. They used a principle component analysis to develop a socio-demographic index for urban flood hazard. A study by Balica et al. also examined flood-related vulnerability by considering geological exposure and the social, economic, and institutional status of an area (*8*). The analysis was conducted at the city level; however, vulnerability varies spatially across the city at finer levels (e.g., TAZ). The abovementioned studies are static in nature and utilized cross-sectional information. On the other hand, the integrated urban systems model dynamically simulates different longer-term decision processes. It captures the changes in neighborhood composition in relation to population, socio-economic and demographic changes, and auto ownership; however, these aspects have often been overlooked in vulnerability assessment modeling. Chakraborty et al. studied evacuation risk by considering "social" and "accessibility to resource" attributes (*9*). Yu-ting and Peeta considered natural hazards and network supply attributes to determine emergency planning zones (*10*). The urban systems model can enhance the reliability of the vulnerability assessment given that the vulnerability can be measured by the degree to which societies or individuals are potentially threatened. For example, a marginalized group of people is likely to suffer from an evacuation. Over the past several years, transportation researchers have been attempting to design and evolve land use modeling systems, for example, "UrbanSim," a macroeconomic model of location choice of households and firms (*11*). This executes macroeconomic and travel demand models, household and employment mobility, and location choice models to forecast the way that demographics change and travel conditions evolve in parallel. Another integrated urban modeling system named "Integrated Land Use, Transportation, Environment" (ILUTE) is used to predict: land development; location choice of households, firms, and workers; vehicle ownership of households; and travel conditions (*12*). Similarly, an integrated urban model named "Integrated Transport Land Use and Energy" (iTLE) assumes that individuals and households are the agents and parcels are the objects (*13*, *14*). iTLE evaluates how people's location choice behavior and vehicle ownership evolve at different life stages. Such long-term simulators can anticipate residential location choice, vehicle ownership, and travel behavior of households over time. These life-stage decisions are determinants of the vulnerability of a group of people or locality during a natural disaster and related evacuation phenomena.

Another major concern is that network disruption is hardly considered in evacuation operation studies.

Moreover, existing network disruption studies focus on small scale areas. For example, Dehghanisanij et al. determined the efficiency of disrupted and undisrupted network of fourteen links (*15*). They conducted a condition-based analysis and estimated a ratio regarding transport-related measures, such as vehicle miles travelled in disrupted and undisrupted networks. Tang and Huang assessed connectivity in relation to degree of road blockage for a network of nine major roads and eight intersections considering a seismic activity (*16*). The evacuation problem is widely studied from a traffic operation perspective utilizing a traffic microsimulation modeling approach (*17–19*). Several evacuation studies have evaluated the strategy of limited access to some facilities and roads to improve the total evacuation time and the time required to only evacuate the population within the most dangerous areas (*20*, *21*). However, to consider network disruptions for a mass evacuation, it warrants traffic model of the entire network that dynamically evolves at a finer-grain time step. Particularly, a DTA-based microsimulation model is of paramount importance to capture routing policies and congestion propagation, which is limited in a large area evacuation modeling. Few studies have taken integrated approaches, which include models for evacuation decisions and transportation choice dimensions, i.e., departure time and route choice (*22*, *23*). These studies combined activity-based models with traffic simulation models. One of the current authors' earlier contributions also developed a sequential modeling framework that includes a flood risk model, a regional transport network model, and a traffic microsimulation model (*24*). However, vulnerability assessment requests the distribution of population in different time periods, which is absent within these sequential evacuation modeling frameworks. This research aims to fill the gap by combining an integrated urban systems model and the sequential modeling approach that offers reliable information on the condition of flood flows, demographic changes, network disruptions, and traffic patterns for the vulnerability assessment (*24*).

Many studies have contributed to the research on vulnerability assessment (*4*, *5*, *8*, *9*). Methods used in these studies include indicator-based flood vulnerability assessment, construction of GIS-based composite vulnerability index, estimation of general flood vulnerability index using a simple averaging method, and GIS-based risk score assignment. The limitation of these methods is that they cannot capture the uncertain features of vulnerability. They are unable to address the causal relationships among various elements of vulnerability. Moreover, they generally perform a single-directional vulnerability assessment at a time. On the other hand, BBN modeling can compute the posterior probability of unobserved variables depending on the variables that are observed. It can capture multi-directional causal relationships obtained from the integrated modeling systems and estimate various vulnerabilities in a single framework to determine the overall risk of the system. BBN modeling has recently been evolved and applied in the field of infrastructure system for risk and reliability analysis (*25*). However, its application in the transportation sector has not yet been explored. Moreover, weighting factors of variables of interest can be used within the BBN modeling framework to consider the relative influence of variables on overall vulnerability (*26*). This study couples AHP with the BBN model to identify the riskiest zones during an evacuation in Halifax, Canada.

Methodology

Integrated Microsimulation-Based Evacuation Modeling Framework

This study develops a framework of an integrated microsimulation-based evacuation model for vulnerability assessment. Vulnerability assessment offers an opportunity to identify risky zones. To accomplish this task, this study integrates three components; (i) an integrated urban systems model, (ii) a flood risk model, and (iii) a DTA-based evacuation microsimulation model. The urban systems model includes a long-term simulator and a regional transport network model, as shown in Figure 1. The long-term simulator generates a synthesized population and addresses residential location choice and vehicle transaction behavior over the life course of the households (*13*). The model microsimulates key household decisions for 15 years ranging from 2007 to 2021, using 2006 as the base year. This model examines how key life stage transitions evolve over time, which is an important determinant of the vulnerability assessment. This study uses the urban systems model results from 2011 to test the efficacy of the proposed framework. The regional transport network model estimates evacuation demand, which determines risk regarding logistical constraints and populates traffic flow within the microsimulation model. A flood risk model informs both the vulnerability assessment and the microsimulation model about flood severity and network disruptions. Microsimulation of evacuation scenarios generates network supply constraints for the estimation of mobility vulnerability. Details of traffic microsimulation and flood risk models can be found in Alam et al. (*24*). The regional transport network model is described in Bela and Habib (*27*).

This study adopts an integrated approach of BBN modeling and AHP to develop the vulnerability assessment framework. The study will examine the development of the vulnerability assessment model utilizing the

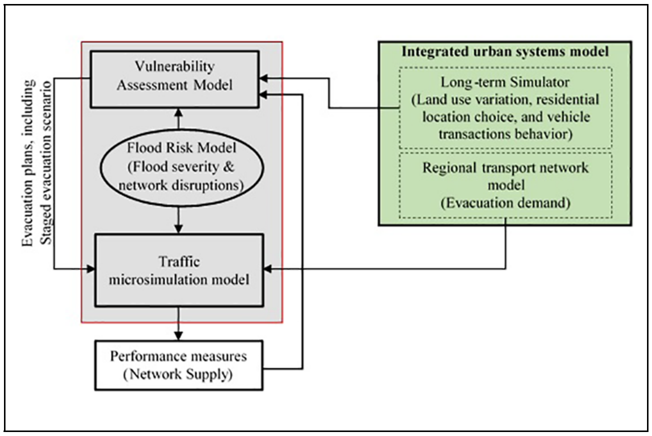

Figure 1. An integrated microsimulation-based evacuation modeling framework.

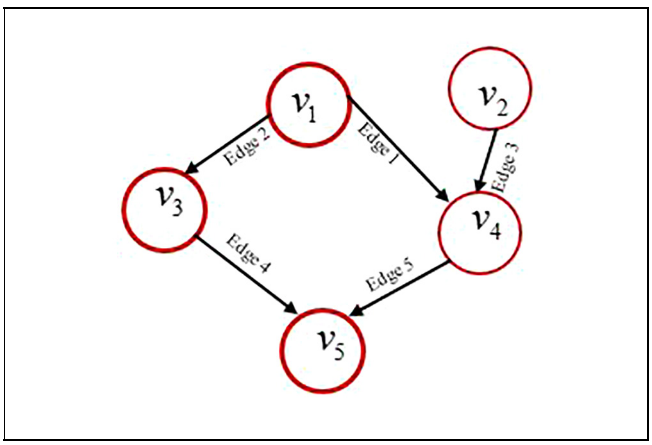

Figure 2. An example of BN incorporating five variables.

inputs from the urban systems model, flood risk model, and traffic microsimulation model, and analyze the risk results that will be obtained from the application of the proposed framework.

Modeling Approach for Vulnerability Assessment

This study has adopted a BBN modeling approach, which is based on Bayes Theorem. It essentially estimates the probability to measure the lack of knowledge regarding the occurrence or non-occurrence of an event. The study utilizes a Bayesian Network (BN) to compute the posterior probability of unobserved variables depending on the evidence of observed variables. In this study, uncertain variables are presented as nodes and casual relationships between nodes or variables are depicted as an edge connecting two nodes. Conditional probability tables (CPT) are developed to determine the strength of relationships between variables. The BN that is developed in this study is a directed graph, which does not allow any cycle in it.

For the vulnerability assessment, let us assume a simple BN as shown in Figure 2, which includes a set of variables (e.g., v_1 = no vehicle ownership, v_2 = presence of seniors in household, v_3 = flood severity, v_4 = clearance time, $\ldots\ldots\ldots v_n$), $V = \{v_1, v_2, v_3 \ldots\ldots\ldots\ldots\ldots v_n\}$. The relationships between variables are represented by edges from node v_i to v_j. For example, edge 1 from v_1 to v_4 provides the conditional probability $p(v_4|v_1)$ indicating v_4 is dependent on the value of v_1. As the edge goes out from v_1 to v_4, v_1 is called a parent node of v_4 and v_4 is called a child node of v_1.

Nodes which have no parent nodes are known as root nodes e.g., v_1 and v_2, and nodes having parent nodes, but no child nodes are called leaf nodes, e.g., v_5. The rest are known as intermediate nodes (e.g., v_3 and v_4). Given the conditional probabilities (e.g., $v_4|v_1$, $v_4|v_2$), the full joint probability of BN for n variables, $v_1, v_2, v_3 \ldots\ldots\ldots\ldots\ldots v_n$, can be estimated using the following equations:

$$p(v_1, v_2, v_3 \ldots\ldots\ldots\ldots\ldots v_n) = p(v_1|v_2, v_3 \ldots\ldots\ldots v_n)p(v_2|v_3, v_4 \ldots \ldots v_n) \ldots\ldots\ldots p(v_{n-1}|v_n)p(v_n) = \prod_{k=1}^{n} p(v_k|v_{k+1} \ldots\ldots\ldots v_n) \tag{1}$$

However, each node is conditionally independent of its non-descendants, given its immediate parent nodes. In that case, Equation 1, for full joint probability, can be transformed into the following equation where each node is conditioned over its parents.

$$p(v_1, v_2, v_3 \ldots\ldots\ldots\ldots\ldots v_n) = \prod_{k=1}^{n} p(v_k|(v^{v_k}_{parents,i}) \tag{2}$$

where $v^{v_k}_{parents,i}$ is a set of all parent nodes of variable v_k

One of the notable features of the BBN model is that it can update the belief of any variable by observing evidence of other variables. For example, the conditional probability of variable, v_1, given the evidence, $E = \{v_2, v_3 \ldots\ldots\ldots\ldots\ldots v_n\}$, can be calculated as follows:

$$p(v_1|E) = \frac{p(v_1, v_2, v_3 \ldots\ldots\ldots\ldots\ldots v_n)}{p(v_2, v_3 \ldots\ldots\ldots\ldots\ldots v_n)} \tag{3}$$

Additionally, the relative importance of risks and the associated risk factors can be imported into BBN to identify the most significant risk.

To determine the degrees of the impacts of vulnerability variables, this study has adopted an AHP approach (*25*). The proposed approach uses a scale ranging from 1 to 9 to make judgment for pairwise comparison of the variables (*28*). To determine the potential inconsistency in judgment, a consistency ratio (*CR*) is estimated utilizing the eigenvector method (*29*). First, a consistency index (*CI*) (used to measure the inconsistency of pairwise comparison) can be estimated using the following equation:

$$CI = \frac{\gamma_{\max} - \eta}{\eta - 1} \quad (4)$$

where $\gamma_{\max}$ is the largest eigenvalue in reciprocal matrix, and η is the number of rows or columns. $\gamma_{\max}$ is always greater than or equal to η. Three conditions together represent an instance of complete consistency, which includes (*28*):

$$\text{(i) } x_{ij}{}^{*}x_{jk} = x_{ik}(\forall i, j, k) \quad (5)$$

$$\text{(ii) } \gamma_{\max} = \eta \quad (6)$$

$$\text{(iii) } CI = 0 \quad (7)$$

where x_{ij} represent the values in the comparison matrix. If there exists no absolute consistency in experts' judgments, then $\gamma_{\max} > \eta$ and the following equation of *CR* can be used:

$$CR = \frac{CI}{RI} \quad (8)$$

Random index (*RI*) is the average value of *CI* for a random matrix. This random matrix can be obtained from Forman (*30*). A *CR* value greater than 0.1 requires revision of the judgment in the matrix because of inconsistent treatment of a factor rating.

The vulnerability of areas is then determined utilizing the proposed modeling approach in light of information obtained from an integrated urban systems model, a flood risk model, and a traffic microsimulation model.

Empirical Application of the Proposed Framework

Determination of Variables Affecting Vulnerability

To develop a set of variables within the BBN modeling framework for vulnerability assessment, this study relies on earlier studies that specifically focused on identifying factors affecting vulnerability. In total, 29 variables that affect social vulnerability are analyzed and are made concise into six variables for the vulnerability assessment during an evacuation. A brief review of variables can be found in Wood et al. (*4*). The socio-demographic variables identified in this study are: presence of female, children, and seniors in a household, household size and income, and no vehicle ownership. Extra safety awareness is perceived if female and children are present in household during an evacuation (*31*). Females are more vulnerable than men if they are in the role of primary caregiver to children and seniors who need assistance, which can prevent females from seeking safe places during an evacuation. The presence of seniors decreases evacuation rates, as they are more likely to have physical impairments and medical conditions that can limit their mobility, which enables a higher-risk household. Larger households experience high logistic constraints. Another key factor for assessing vulnerability is income, which affects vehicle ownership of a household. "No vehicle ownership" raises concerns regarding transportation arrangements to evacuate the transit-dependent population.

Flood severity and distance of a zone to the flood source are important measures for assessing the degree of vulnerability of that area (*31*). The flood risk model used in this study revealed that a higher flood severity and a zone's proximity to a flood source can cause higher inundation of the area and network links (*15*). Moreover, house type is another crucial factor that influences susceptibility to natural disasters. Because of the nature of construction, mobile houses are more likely to suffer from flood or storm damages (*32*).

This study uses clearance time, demand density, and zone-to-exit distance to determine the degree of evacuation complexity. For example, exit closure is likely to increase clearance time, while large population size adds difficulty in evacuation because of the requirements of extensive logistic support (*10*). Given the factors and causal relationships of the variables described above, the proposed BBN modeling framework is presented in Figure 3 followed by the estimation of the variables.

Estimation of the Variables for BBN Model

Estimation of the Social Vulnerability Variables through Urban Systems Modeling. The long-term simulator used in this study yields socio-demographic variables identified in the previous section for the period of fifteen years (from 2007 to 2021). In this study, presence of children is "True" if the age of any household member is $<$ 18 and "False" if all members are 18 or over. In this case, the age group that is less than 18 represents young adults and children who are deemed to be vulnerable and dependent on others for evacuation. Similarly, for seniors, "True" holds if any age is $>$65 and "False" if all ages are $<$65. The number of females, children, and seniors are predicted for each TAZ of the Halifax Peninsula utilizing the urban systems model. Then, based on the total population in the zone, percentage female, percentage children, and percentage seniors are estimated. In relation to different income categories, percentage households having zero vehicles in a zone is also estimated using a similar technique. According to a study by the United Nations, a household with five members or more can be considered a large household (*33*). The

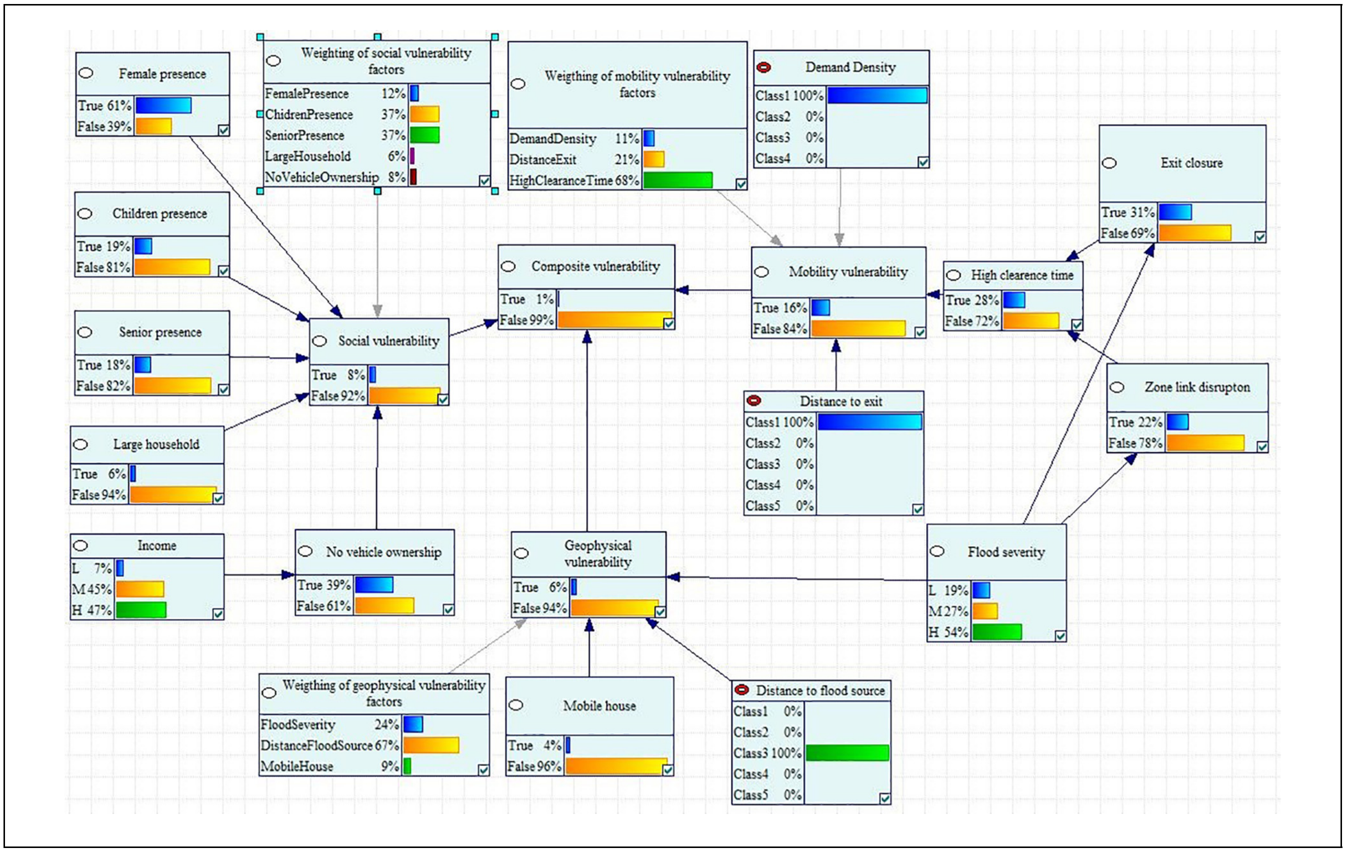

Figure 3. The proposed BBN model for vulnerability assessment of the Halifax Peninsula.

total number of individuals in a household is determined by carrying the IDs of all household members under a unique household ID in the simulator. Based on the number of members in the households, the total number of large households in a zone is estimated. A "True" state is used in the BBN model if the number of household members is greater than or equal to 5 and "False" if it is less than 5.

Estimation of the Geophysical Vulnerability Variables through Flood Risk Modeling. The extent of flooding over the Halifax region is determined utilizing a flood risk model. First, the LiDAR data obtained from Halifax Regional Municipality and Google Street View are used to interpret culverts and bridges correctly within a Digital Elevation Model (DEM). The culverts are then used to notch the DEM to allow a path for water to move, resulting in a hydraulically connected DEM. The flood risk model generates flood layers based on Hurricane Juan and overlays them with Nova Scotia road network to simulate the extent of the inundation over the region. The flood risk model contributes to this study with three flood severity scenarios and identifies network link disruptions by percent of the total link length. Moreover, the model informs if exit closures occur for each flood scenario. Flood severity is measured based on water levels: Low (2.9 m water level), Medium (3.9 m water level), and High (7.9 m water level). The information obtained from the flood risk model is used to determine the posterior probabilities of "exit closure" and "zone-specific link disruption" given their parent node "flood severity." A boolean expression is used in this case. For example, based on flood risk model results, if the flood severity is high, an exit closure is certain, which is represented by a value of 1 in the BBN model. In Table 1, several cases are shown where a boolean expression is used. Two states named "True" and "False" are used where "True" states the likelihood of occurrence and "False" states the non-occurrence of a candidate event.

The geographic location of a zone is also important to assess geophysical vulnerability. The location of a zone with respect to exit and flood source are determined using the 2012 Halifax Geodatabase. Distance of any TAZ to a flood source is inversely related to the degree of impacts that zone experiences. This study introduces five classes of distances for the BBN model, such as: class 1 if distance is $<$ 100 m, class 2 if distance is $>$ 100 m and $<$300 m, class 3 if distance is $>$300 m and $<$500 m,

Table 1. Example of Boolean Expression Used to Determine the Posterior Probabilities for Variables "Zone Link Disruption," "Exit Closure," and "Clearance Time"

Variables	Example of expression and description
Zone-specific link disruption	If (flood severity = High, "True,""False")—if flood severity is high, disruption to links of a zone is true at certain degree of belief
Exit closure	If (flood severity = High, "True,""False")—if flood severity is high, exit closure is true at a certain degree of belief
Clearance time	If (zone link disruption = True, exit closure = True, "True,""False")—if zone link disruption and exit closure occur, clearance time is greater than 1.0 hour with certain degree of belief

class 4 if distance is >500 m and <1000 m, and class 5 if distance is >1000 m, to measure the geophysical vulnerability. Distance is considered as a deterministic variable for BBN modeling.

Estimation of the Mobility Vulnerability Variables through Evacuation Microsimulation Modeling. To obtain the zonal clearance time, a microsimulation model developed by Alam et al. is updated and utilized to simulate evacuation scenarios (*24*). The "clearance time" required to evacuate each zone on the Peninsula is determined through the simulation. A higher clearance time poses a higher level of risk to safely evacuate residents (i.e., mobility vulnerability). The updated traffic evacuation microsimulation model of the Halifax Peninsula has five entry-exit points for evacuation. The exits include two bridges, two highways, and a roundabout. The network model contains 1784 links and connectors that result in a road network with a total length of 480 km, 41 major signalized and stop sign-controlled intersections with 2813 resolved turning conflicts in the network. The model treats areas as TAZ and simulates the evacuation of 56 TAZs on the Peninsula. The zoning system used in this study is in alignment with the zoning system of the Halifax Transport Network Model developed by Bela and Habib (*27*). The Halifax Transport Network Model is utilized to estimate the evacuation demand on the Peninsula. After the simulation, the total time required to evacuate each TAZ is recorded. A boolean expression is used to obtain the posterior probability of "clearance time" given its parent nodes, "zone link disruption" and "exit closure" (see Table 1). A state "True" is used for BBN modeling if the clearance time is "High," meaning clearance time is $>$ 1 hour, otherwise, "False" is used.

Moreover, greater distance to exit and higher demand density also elevate the mobility complexity during an evacuation. In this study, distance to exit is indexed as class 1 if distance is $<$ 1.0 km, class 2 if distance is $>$1.0 km and $<$2.0 km, class 3 if distance is $>$2.0 km and $<$3.0 km, class 4 if distance is $>$3.0 km and $<$4.0 km, and class 5 if distance is $>$4.0 km. Demand density is also normalized into five classes, such as class 1: 0–0.2, class 2: 0.2–0.4, class 3: 0.4–0.6, class 4: 0.6–0.8, and class 5: 0.8–1.0. The probabilities for nodes "social vulnerability", "geophysical vulnerability" and "mobility vulnerability" in the BN are determined by the weighted sum of probabilities of their "parent nodes." A label type node representing the weights of each variable is introduced in the BN. Such weights can be obtained from engineering judgment, expert knowledge, or both, using any of the different decision analysis techniques. This study combines AHP with BBN to incorporate weights for each variable in the BN-based vulnerability assessment modeling. The conditional probability table for the node of composite vulnerability is derived by the weighted sum of social, geophysical, and mobility vulnerability and then composite vulnerability is measured.

Weighting of Variables for BBN Model

This study utilizes AHP to determine the weighting factors for all variables of three vulnerabilities. For demonstration purposes, the weighting of variables affecting social vulnerability is presented in Table 2. For social vulnerability, AHP follows a four-step approach and V1 stands for "female presence," V2 for "children presence," V3 for "senior presence," V4 for "large household," and V5 for "no vehicle ownership." All the resulting weighting factors of variables of three vulnerabilities with consistency ratio are presented in Table 3.

Results and Discussions

Vulnerability Assessment Results

This study develops a composite vulnerability as well as social, geophysical, and mobility vulnerability. It identifies risky zones based on the model results, as presented in Figure 4 (*a–d*). The results reveal that vulnerable zones are found to be sporadically located at the north- and south-end of the Peninsula, the downtown core, and the Quinpool and Mumford areas. Figure 4*a* shows that the north-end of the Peninsula is significantly vulnerable in

Table 2. Four-step AHP for Weighting Factors of Five Variables Affecting Social Vulnerability

Step 1: Pairwise comparison of variables based on scale 1–9

	V1	V2	V3	V4	V5
V1	1	1/3	1/3	3	1
V2	3	1	1	7	5
V3	3	1	1	7	5
V4	1/3	1/7	1/7	1	1
V5	1	1/5	1/5	1	1
Sum	8.333	2.676	2.676	19	13

Step 2: Normalization of the matrix in step 1 and setting priority by taking average of each row

	V1	V2	V3	V4	V5	Priority
V1	0.120	0.124	0.124	0.158	0.077	0.121
V2	0.360	0.374	0.374	0.368	0.385	0.372
V3	0.360	0.374	0.374	0.368	0.385	0.372
V4	0.040	0.053	0.053	0.053	0.077	0.055
V5	0.120	0.075	0.075	0.053	0.077	0.080
Sum	1	1	1	1	1	1

Step 3: Weighted sum estimation by multiplying criteria weight with each cell in step 1 and taking sum of each row

	V1	V2	V3	V4	V5	Weighted sum
Criteria weight	0.121	0.372	0.372	0.055	0.080	na
V1	0.121	0.124	0.124	0.166	0.080	0.614
V2	0.362	0.372	0.372	0.387	0.399	1.892
V3	0.362	0.372	0.372	0.387	0.399	1.892
V4	0.040	0.053	0.053	0.055	0.080	0.282
V5	0.121	0.074	0.074	0.055	0.080	0.405

Step 4: Calculate maximum Eigen value and consistency ratio

Weighted sum	For priority in col 2	For priority in col 3	For priority in col 4	For priority in col 5	For priority in col 6	Average Eigen value
na	na	na	na	na	na	na
0.614	0.121	4.957	4.957	3.704	7.696	4.676
1.892	5.224	5.086	5.086	4.891	4.742	5.072
1.892	5.256	5.064	5.064	5.136	4.920	5.130
0.282	7.007	5.294	5.294	5.096	3.530	5.673
0.405	3.351	5.438	5.438	7.320	5.070	5.387

Maximum Eigen value = 5.188

Number of variables, n = 5, and random index = 1.12

Consistency index = (5.188-5)/(5-1) = 0.047

Consistency ratio = 0.047/1.12 = 0.042

Note: na = not applicable.

Table 3. AHP-based Weight Assignment to Variables of Different Vulnerabilities and Consistency Ratios

Vulnerability class	Variables	Weight assigned	Consistency ratio
Social vulnerability	Female presence	0.12	0.042 < 0.1
	Children presence	0.37	
	Senior presence	0.37	
	Large household	0.06	
	No vehicle ownership	0.08	
Geophysical vulnerability	Flood severity	0.24	0.01 < 0.1
	Distance to flood source	0.67	
	Mobile house	0.09	
Mobility vulnerability	High clearance time	0.68	0.05 < 0.1
	Demand density	0.11	
	Distance to exit	0.21	

relation to composite vulnerability. The composite vulnerability of this end is dominated by social and mobility vulnerability as seen in Figure 4*b* and Figure 4*d* respectively. Similarly, several zones located by Quinpool and Mumford road are low-income areas and are found to be significantly socially vulnerable (Figure 4*b*). The mobility vulnerability of these zones is also observed to be significant (Figure 4*d*). The social vulnerability is likely to be concentrated at the downtown core and two ends of the Peninsula. The vulnerability results suggest that zones that are socially vulnerable are a result of the presence of females and seniors in those zones. In addition, "no vehicle ownership" status of the household adds to evacuation risk of a zone. The proportion of females is around 44–64% for all Peninsula TAZs. In the case of the highly vulnerable locations identified above, the proportion of seniors in the population is observed to be greater than 39%. A few TAZs in the north-end area show a senior population proportion of 25%, while the rest of the TAZs have under 20% seniors. The proportion of "no vehicle households" on several north-end and downtown core zones ranges between 33% and 43%, while it is typically 20–25% or less for the rest.

Analysis of Relative Impacts of Variables Affecting Vulnerability

To examine the relative impacts of a specific variable in determining vulnerability, this study conducts a sensitivity analysis for the variables of all three different vulnerabilities. For demonstration purposes, this study presents the impacts of variables of social vulnerability. To analyze the impacts of causal factors of social vulnerability, the node "social vulnerability" is set as the target node in BN and the impacts of its causal factors are measured in relation to conditional probability. Initially, tornado diagrams are created to determine the impacts of variables on social vulnerability over each TAZ. Impact results of all individual TAZs are then aggregated to show how the impacts of different variables on social vulnerability differ spatially over the Halifax region in Canada. An example of a tornado diagram for certain TAZs (e.g., zone ID-17, 90, 95, and 100) is shown in Figure 5, where a variable with a longer bar reflects higher influence on vulnerability than variables with a shorter bar. The diagram shows the most sensitive parameters for a selected state of a target node (in this case, "True state" for target node "social vulnerability") sorted from the most to the least sensitive. The number of parameters shown in Figure 5 can be selected between top 10 and all. For the sensitivity analysis, the percentage of change in all parameters is considered to be 10%. The horizontal axis shows the absolute changes in the posterior probability of social vulnerability for the state "True" when each of the parameters changes by that percentage. The influence of the variables in relation to changing the vulnerability across TAZs can be derived from this diagram 5.

Figure 6 shows how the degree of impacts of different variables (with a change of 10% in their current values) on the social vulnerability vary spatially over the Halifax region. Depending on the degree of impacts of a variable corresponding to a TAZ (a spatial unit), the variable is assigned a rank in the parameter list of the tornado diagram, which is used as the "spatial ranking" in this study. A graduated color scale is used where the darkest color represents a rank of 1, meaning the highest change in social vulnerability because of changes in the variable, and the lightest color represents a rank of 5, meaning the least change caused by the changes in variable. The results show that the variable, "female presence" is a key determinant of social vulnerability. This variable ranks first to third in the list of the parameters of the tornado diagram for the absolute changes in social vulnerability of different TAZs. However, for the majority of the TAZs, it ranks first. The variable "senior presence" is found to be the most impactful variable for several TAZs in the core and the north- and south-end of the Peninsula. "Children presence, " and "no vehicle

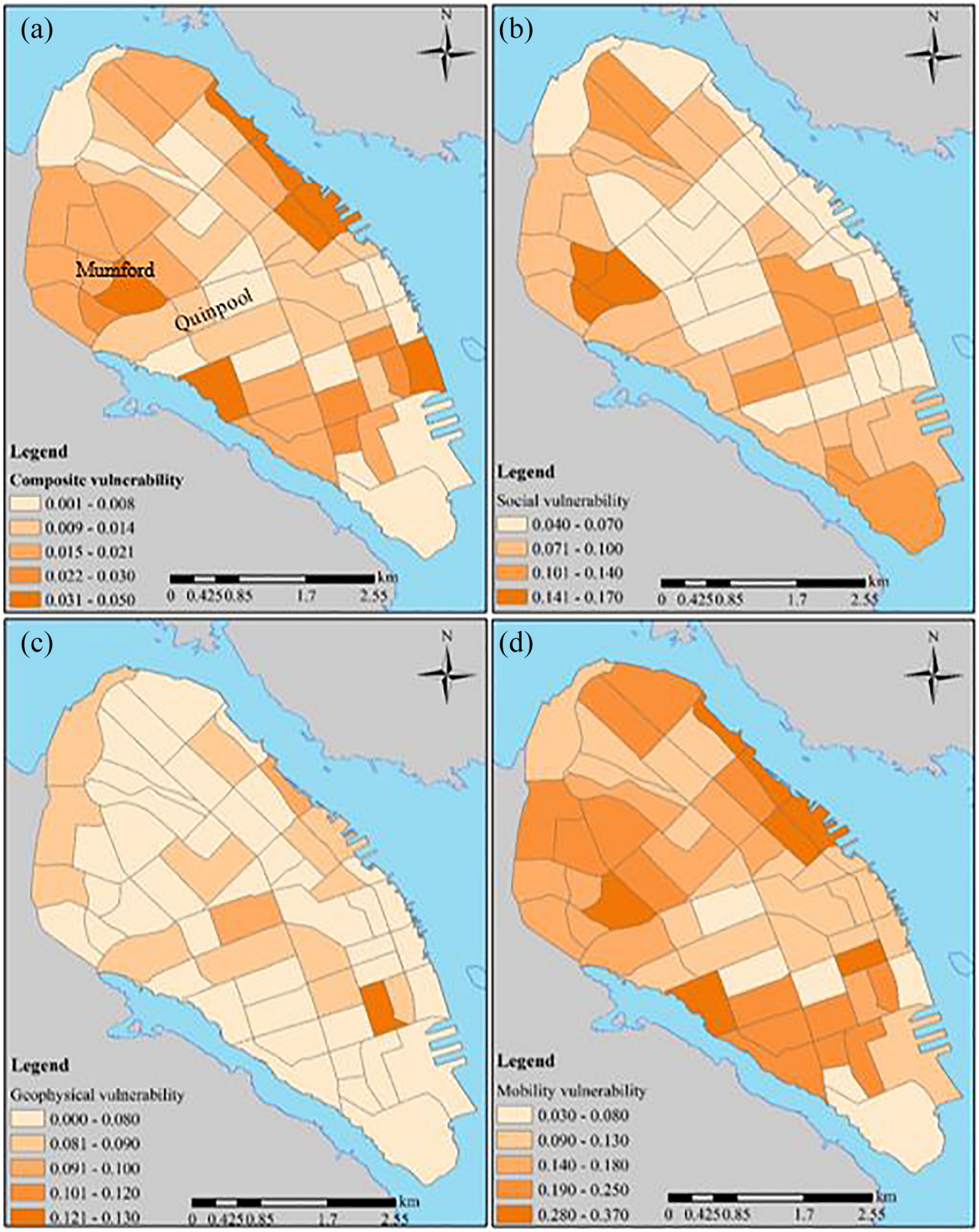

Figure 4. Vulnerability assessment in the Halifax Peninsula, including (*a*) composite, (*b*) social, (*c*) geophysical, and (*d*) mobility vulnerability.

ownership" sporadically contribute to social vulnerability. Variable "large household" is found to be dominant in several downtown zones for the social vulnerability. The results suggest that "presence of seniors and children," and "large household" variables impact social vulnerability taking a rank in the parameter list from 1 to 5

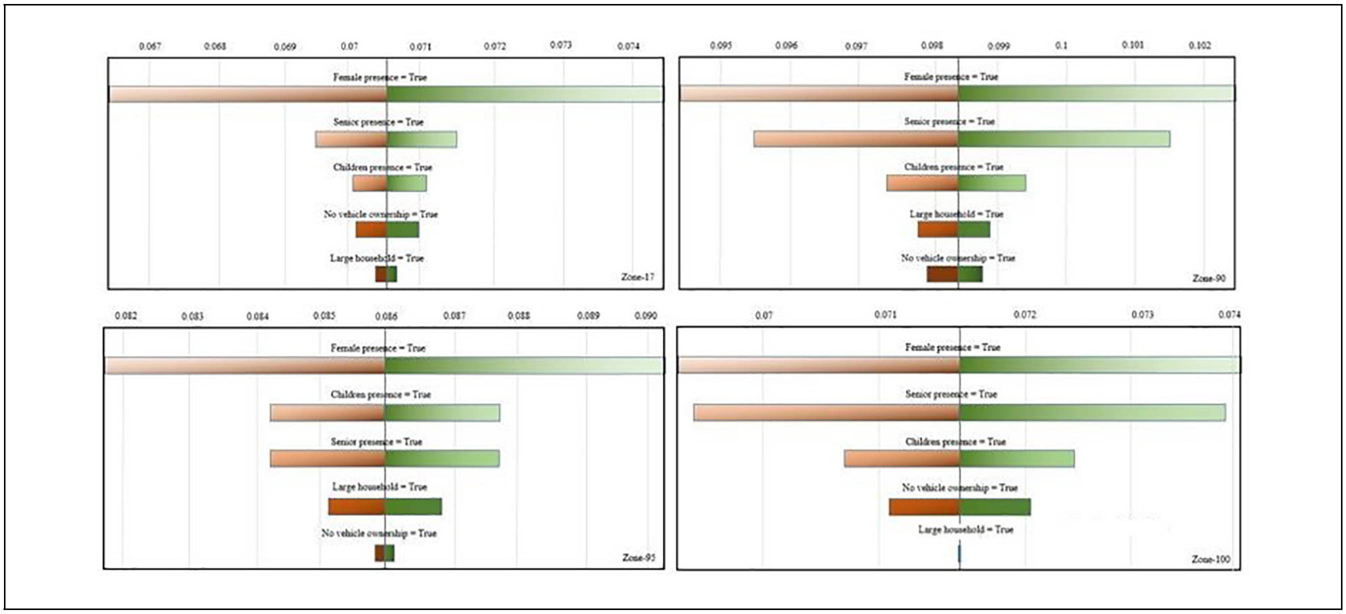

Figure 5. Tornado diagram for sensitivity analysis of vulnerability variables.

while “no vehicle ownership” holds its position from 1 to 4. This study also evaluates the relative impacts of the respective variables on geophysical and mobility vulnerability. “Flood severity” and “clearance time” are found to be the most impactful variables in the cases of geophysical and mobility vulnerability respectively.

Conclusion

This study presents an integrated microsimulation-based evacuation modeling framework to conduct a vulnerability assessment. The novelty of this study is that it combines an integrated urban systems model and a traffic microsimulation model, which offers a unique opportunity to develop evacuation plans for future years. The proposed framework utilizes the information related to changes in population distribution, auto ownership, and traffic flows. One of the unique features of this study is that it utilized a BBN modeling approach for a vulnerability assessment, while addressing uncertainty and causal relationships in different elements of the vulnerability.

The proposed framework was empirically tested for a case study of Halifax, Canada. This study determined risky TAZs over the Halifax Peninsula in the light of information obtained from an urban systems model, a flood risk model, and traffic microsimulation model. Three vulnerabilities (social, geophysical, and mobility) were analyzed followed by developing a composite vulnerability within the integrated modeling framework. The relatively crucial factors identified by AHP were the presence of females, seniors, and children in households for the estimation of social vulnerability, and flood severity and clearance time for the geophysical and mobility vulnerability respectively. The probability estimation process has been enhanced by including the importance of the risk and the risk factors in the BBN model. The BBN approach identified mobility as a critical source of vulnerability for the Halifax Peninsula during an evacuation. Zones located on the periphery of the Peninsula, far from the exits, or both, are highly vulnerable in term of mobility. Composite vulnerability is found to be sporadically concentrated at the north- and south-end of the Peninsula, the downtown core, and the Quinpool and Mumford areas. A sensitivity analysis with a change of 10% in the values of each variable was conducted for an understanding of the impacts of variables on the respective vulnerability. The sensitivity results revealed that the female and senior population distribution of a zone are key determinants of social vulnerability. Flood severity and the high clearance time are two other impactful factors of geophysical and mobility vulnerability respectively.

This study contributes to the integration of an urban systems and a traffic microsimulation model to incorporate long-term socio-demographic characteristics and mobility aspects into the vulnerability assessment. The study has some limitations. For example, it only used the results of a 2011 urban systems model. Since this study has used an integrated modeling framework, it can determine multi-year vulnerabilities for comparison in a future study. Additionally, testing of an evacuation improvement strategy, including a staged evacuation that would be informed by the proposed integrated evacuation microsimulation model, could be interesting. The

Figure 6. Degree of sensitivity of each variable of social vulnerability over Halifax region where (*a*) female presence, (*b*) children presence, (*c*) senior presence, (*d*) large household, and (*e*) no vehicle ownership.

proposed model results will help to understand the spatial shifting of vulnerable areas within a time horizon. The results will inform the prioritization of areas based on a vulnerability index, which can be the basis of zonal demarcation. Zonal demarcation enriched with vulnerability information can assist a staged evacuation that would help minimize casualties, particularly focusing on residents with mobility issues and carless populations. The results of this research will help emergency professionals and engineers to develop policies for resolving ethical dilemmas during spatial prioritization of an evacuation.

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Author Contributions

The authors confirm contribution to the paper as follows—study conception and design: MAH, MJA; data collection: MJA, MAH; analysis and interpretation of results: MJA, MAH; draft manuscript preparation: MJA, MAH. Both authors reviewed the results and approved the final version of the manuscript.

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