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# Evacuation Zone Modeling under Climate Change: A Data-Driven Method

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**ABSTRACT**

Pre-determined evacuation zones can be used to estimate the demand of evacuees, which is helpful in assessing the resilience of transportation systems in the presence of natural disasters. Evacuation zones defined based on current road networks, environmental and demo-economic characteristics of a region cannot remain the same in the future, since the long-term climate change such as the rise of sea level would have major impacts on hurricane-related risks. Traditional methods for the prediction of future evacuation zones rely heavily on the storm surge models and could be time-consuming and costly to use. This study develops a novel grid cell-based data-driven method which can predict future evacuation zones under climate change without running the expensive storm surge models. The map of Manhattan, which is the central area of New York City (NYC), was uniformly split into 45×45 $m^2$ grid cells as the basic geographical units of analysis. A decision tree and a random forest were used to capture the relationship between grid cell-specific features such as geographical features, evacuation mobility, and demo-economic features and current zone categories which could reflect the risk levels during hurricanes. Ten-fold

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cross-validation was used to evaluate model performance and it was found that the random forest outperformed the decision tree in term of the accuracy and Kappa statistic. The random forest was used to predict the delineation of evacuation zones in the 2050s and 2090s, based on the predicted sea level rises and changes of demo-economic features. Compared with the current zoning, the areas with need of evacuation are expected to expand in the future. The proposed method can be used to promptly estimate the future evacuation zones under different sea level rise scenarios and can provide the convenience to assess transportation system resilience in the context of climate change.

***Keywords:*** Evacuation Zone, Emergency Management, Resilience, Random Forest, Hurricane, Climate Change

## INTRODUCTION

Hurricanes can devastate coastal areas with flooding, high wind, and rainfall, resulting in serious loss of lives and property. It is important for emergency planners to define evacuation zones which can indicate inhabitants whether or not they are prone to hurricane-related risk in advance of disaster impacts Pre-determined evacuation zones can be used to estimate the demand of evacuees, which is helpful in assessing the resilience of transportation systems. The term resilience has been used in a variety of domains ranging from ecology to infrastructures systems (Ayyub 2014; Francis and Bekera 2014; Holling 1973; Linkov et al. 2014; Park et al. 2013; Vugrin et al. 2011). In this study, resilience is defined as the ability of the transportation systems to maintain certain level of service under hurricane evacuation scenarios. Similar definition can be seen in Heaslip et al. (2010), and this definition reflects the absorptive capacity - the degree to which a system can mitigate the impact of adverse events - of systems, which is one of three pillar resilience capacities as stated in Francis and Bekera (2014). Since the long-term climate change could have major impact on hurricane-related risks, evacuation zones defined based on current network, environmental and demo-economic characteristics of a region cannot remain the same in the future. One notable factor of climate change is global warming and the resulting rise of sea level. According to the study of the United States Geological Survey in 2012, the sea level of the Atlantic coast of North American rose by 1.97–3.80 mm per year since 1990 (Sallenger Jr et al. 2012). The rise of sea level in the future is likely to promote the flooding risk for coastal areas. Therefore, it is essential to consider the impact of climate change on evacuation zone determination when evaluating the transportation system resilience.

A framework for assessing the resilience of transportation systems with respect to climate change is presented in Fig. 1. Future evacuation zones can be estimated based on climate change and the developed evacuation zone prediction model. Knowing the population in the evacuation zones and their evacuation behaviors (the specific decisions of whether or not to evacuate, where to evacuate, etc.), we could estimate the evacuation demand. A recent study by Yang et al. (2016) uses structural equation models to jointly estimate evacuation decision choices and the evacuation destination choices. Evacuation demand along with the background traffic are used as inputs for evacuation simulation. A recent study by Zhu et al. (2016) presents evacuation simulation with consideration of traffic incident-induced highway capacity loss. The level of services under different climate change scenarios can be estimated using the outputs of evacuation simulation, and thus the resilience of transportation systems can be assessed.

<Insert Figure Here>

**Fig. 1.** Framework for assessing the resilience of transportation systems under climate change

Manhattan, which is the central area of New York City (NYC), is used as a case study. NYC is a city vulnerable to hurricanes. The NYC evacuation zones were updated in 2013 by using the latest high-resolution SLOSH (sea, lake, and overland surges from hurricanes) models from the National Weather Service. The new zoning model incorporates improved elevation data, accounts for the accessibility of the neighborhoods by bridges and roads and consider the scenarios when storm surge coincide with high tide (NYC 2013). According to NYC Office of Emergency Management, NYC has about 966 km of coastline and almost 3 million people living in the areas at the risk of hurricanes (Gregory 2013). Considering the larger number of vulnerable coastal population, it is essential to define up-to-date evacuation zones for the development of detailed evacuation plan. Hurricane Sandy, which made landfall in October 2012 and is the second-costliest hurricane in United States history (Xie et al. 2015), provides us valuable data to study.

This study focuses on the prediction of future evacuation zones in the context of climate change. To predict future evacuation zones, traditional methods rely on the estimation of surge flooding using models such as the SLOSH model and the ADCIRC (a parallel advanced circulation model for oceanic, coastal, and estuarine waters) model (Wilmot and Meduri 2005). However, the implementation of the SLOSH and ADCIRC models can be really time-consuming and costly. For example, multiple runs of the SLOSH model need to be executed to determine the maximum water elevation under scenarios with different land fall points and storm intensities (Wilmot and Meduri 2005). Thereby, we propose a novel data-driven method that can predict future evacuation zones under different climate change scenarios, without running expensive storm surge simulations. Machine learning algorithms are used to establish the relationship between current pre-determined evacuation zones and hurricane-related factors, and then to predict how those zones should be updated as those hurricane-related factors change in the future. Moreover, a special consideration is given to the demo-economic factors such as the disability and poverty, since communities with more vulnerable populations are known to be at higher risk when confronting hurricanes.

## LITERATURE REVIEW

Evacuation planning is a thematic research topic, particularly after a number of natural disasters such as recent hurricanes Irene and Sandy on the east coast. There have been a large number of research studies on related issues such as shelter location, transportation routing and medical service in evacuation planning. However, only a limited number of studies are available on the determination of evacuation zones.

Generally, hurricane evacuation zones are determined based on the risk of flooding. Wilmot and Meduri (2005) and Meduri (2004) are among the early studies to develop a detailed procedure to delineate hurricane evacuation zones using TransCAD. In the method they proposed, basic zones of evacuation were created based on the key geographic information system (GIS) data including a ground elevation layer, a zip code boundary layer, and land use data. The SLOSH model was used to estimate the storm surge elevations in the study area. The depth of inundation was estimated by subtracting the ground elevation from the predicted surge height in each zone. Their proposed procedure was demonstrated through a case on identifying the hurricane evacuation zones in the New Orleans metropolitan area.

FRPC (2012) identified the evacuation zones in South Florida region according to factors such as storm tide limits, wind vulnerability, population at risk, and flood prone areas (based on 100-year flood zones).

When PBS&J were conducting hurricane evacuation studies in several states (PBS&J 2007a; PBS&J 2007b), the evacuation zones were determined based on the surge inundation limits developed by the US Army Corps of Engineers (USACE) using the SLOSH model. The limits for category 1 through 4 tropical cyclones and the boundaries of the minor civil divisions within each country were used to develop the evacuation zones for various storm scenarios.

Other than hurricane evacuation zones, the National Tsunami Hazard Mitigation Program (NTHMP) (NTHMP 2011) provide some guidelines and best practices for tsunami evacuation mapping. It suggests that the evacuation mapping should consider historical inundation information, select reasonable elevation based on local topography, tectonic setting, and distance from local shorelines, interpolate and extrapolate inundation based on estimated models. In case of no other tsunami hazard information and hurricane storm surge maps, the Storm Surge Atlas Maps in consultation with the NTHMP scientific representative was suggested for tsunami evacuation planning.

Similarly, the practices in Hawaii also provide some valuable experience in evaluating and adjusting evacuation zones. For example, Mader (2010) modeled the hazard of the evacuation zones in Hawaii based on the potential tsunami events. According to the study, both elevation criteria and the Fritz criteria generalized from the surveys were used to check the current evacuation zones in Hawaii (Liu et al. 2005; Mader 2010). The Fritz criteria that defined the evacuation zones are: “(a) areas below 15 m above sea level and within 0.4 km of shoreline or along rivers; (b) areas below 10 m above sea level and within 1.6 km of shoreline or along rivers; and (c) areas below 5 m above sea level and within 4.8 km of shoreline”. Similarly, in order to update the current evacuation zone maps developed in the 1980s, the Fritz criteria have also been used by Meadows (2013) when comparing 3 potential new tsunami evacuation zone delineations for Hawaii.

All the aforementioned studies delineated the evacuations zones based on hydrogeological and / or geographical features such as elevation, surge inundation, and the distance to the shorelines. There are a number of studies exploring the demo-economic factors that put residents at high risk when confronting natural disasters. Zoraster (2010) reviewed 228 articles on vulnerable populations during hurricanes. He summarized risk factors to be considered when planning for disaster preparation, which include poverty, home ownership, poor English language proficiency, ethnic minorities, immigrant status, and high-density housing. Morrow (1999) investigated the examples from Hurricane Andrew and found that “the poor, the elderly, women-headed households and recent residents, are at greater risk throughout the disaster response process”. Chakraborty et al. (2005) used both geophysical risk and social vulnerability indices to assist the development of evacuation strategies. The social vulnerability index is related to factors such as total population, number of mobile homes, population below poverty level, children, the elderly, and population with disabilities. Various studies (Chakraborty et al. 2005; Eldar 1992; McGuire et al. 2007; Ortíz et al. 1986; Rizzo 1977; Sommer and Mosley 1972) suggested that elderly persons and children are more vulnerable to the safety and health hazards of natural disasters. The cut-off ages for defining the elderly differ from 60 (Rizzo 1977; Sommer and Mosley 1972), to 65 (McGuire et al. 2007; Ortíz et al. 1986) and to 85 (Chakraborty et al. 2005). Similarly, cut-off ages for defining children differ from 5 (Chakraborty et al. 2005) to 9 (Rizzo 1977; Sommer and Mosley 1972). In this study, we don’t use the cut-off ages to define the elderly and children. Instead of doing that, the populations in seven different age groups (0-4, 5-9, 10-14, 60-64, 65-74, 75-84, and 85+) are used as predictors in the evacuation zone prediction model, and the relationship between different age groups and hurricane-related risk could be established automatically by the proposed machine learning methods.

Most previous studies on evacuation zoning focus heavily on the implementation of storm surge models. Evacuation zoning is mainly determined by the flooding risk and less consideration is given to other risk factors such as evacuation mobility and demo-economic features. This study aims to use machine learning methods to capture the relationship between evacuation zoning and various hurricane-related factors. The delineation of future hurricane evacuation zones can be estimated even if the outputs from the storm surge models are unavailable. The effects of vulnerable populations such as are accounted for in the proposed evacuation zoning models.

## DATA PREPARATION

The map of Manhattan was uniformly split into a total of 25,440 grid cells with size of 45×45 $m^2$ as the basic geographical units of analysis. The selection of cell size is a trade-off between information precision and computation cost. The width of a standard block in Manhattan is about 90 m and the length of it is about 270 m (both are divisible by 45 m). Using cells with lengths of 45 m can capture cell-specific features more precisely and can provide street-by-street resolution for evacuation management. Zone category, geographical features (e.g. average elevation above sea level), evacuation mobility (e.g. distance to the nearest subway station) and demo-economic features (e.g. total population and population with disability) were obtained for each cell using spatial analysis tools of ArcGIS (Johnston et al. 2001). Detailed description on data collection will be presented in the following paragraphs.

The NYC Hurricane Evacuation Zones Map (http://maps.nyc.gov/hurricane/) was updated in 2013 after Hurricane Sandy. The 2013 evacuations zones are listed from zone

1 to zone 6, from the highest risk to the lowest risk. Each grid cell was attached to its zone category which could reflect the risk level during hurricanes. In this study, four-level zone category is used as the response variable in the proposed machine learning methods, with "E1" corresponding to NYC 2013 evacuation zone 1, "E2" corresponding to NYC 2013 evacuation zone 2 and zone 3, and "E3" corresponding to NYC 2013 evacuation zone 4, zone 5 and zone 6, and "S" corresponding to the safe zone beyond the evacuation region.

Digital Elevation Model (DEM) data of NYC provides a representation of the terrain with elevations above the ground in a regular raster form. The DEM data of Manhattan was extracted from National Elevation Dataset (NED, http://ned.usgs.gov/) developed by U.S. Geological Survey (USGS). The resolution of the DEM data is 1 arc second (about 27 m) and the pixel values are elevations in feet based on North American Vertical Datum of 1988 (NAD83). The average elevation which is associated with the flooding risk was aggregated for each grid cell. Another geographic feature collected for each cell is the distance to the coast, since areas closer to the coast are more likely to be affected by the storm surges.

Evacuation mobility is related to the efficiency of pre-storm evacuation. NYC Office of Emergency Management (OEM) offers shelters during hurricanes in evacuation centers. The distance to the nearest evacuation center was computed for each grid cell of the map. Additionally, transportation mobility such as the distance to the nearest subway station, the distance to the nearest bus stop and the distance to the nearest highway were also obtained by using spatial tools of ArcGIS (Johnston et al. 2001).

In addition to evacuation mobility, demo-economic features can affect the division of evacuation zones. For example, the total population is related with the priority of evacuation, and the zones with large number of disables, elderlies, and children tend to be more vulnerable. Twelve demo-economic features for each census tract were obtained from the U.S. Census Bureau (http://factfinder.census.gov)

The descriptive statistics of predictors including geographic features, evacuation mobility and demo-economic features are presented in Table 1. The spatial distributions of those predictors are demonstrated in Fig. 2.

<Insert Figure Here>

**Fig. 2.** Spatial distributions of predictor

# METHODOLOGY

In this section, we introduce classification tree and random forest models which can be used to explore the pattern of evacuation zoning by using zone category as the response variable and geographic features, evacuation mobility and demo-economic features as predictors. Statistic measures for performance and cross-validation method are also introduced in this section.

## Classification Tree and Random Forest

A classification tree classifies observations by reclusively partitioning the predictor space (Breiman et al. 1984). The classification tree is a non-parametric classifier, and hence no assumption needs to be made on the form of relationship between the predictors and the response variable. The classification tree is capable of capturing the nonlinear relationship between the evacuation zone categories and relevant features. Additionally, the classification tree is able to perform feature selection automatically by maximizing entropy reduction (Breiman et al. 1984). The entropy for the node $m$ is defined by the following equation (Quinlan 1986):

$$Entropy_m = -\sum_{j=1}^{J} p_m^j \log_2 p_m^j \tag{1}$$

where $J$ is the total number of classes and $p_m^j$ is the proportion of the class $j$ $(j = 1, 2, ..., J)$ on the node $m$. $p_m^j$ can be obtained by:

$$p_m^j = \frac{N_m^j}{N_m} \tag{2}$$

where $N_m$ denotes the number of instances at the node $m$ and $N_m^j$ is the number of instances belong to the class $j$. The largest entropy on the node $m$ is $\log_2 J$. If node $m$ is not pure, it should be split to reduce the entropy. If $N_{m,p}$ of $N_m$ take the branch $p$, the entropy after the split is given as:

$$Entropy_m^{'} = -\sum_{p=1}^{P} \frac{N_{m,p}}{N_m} \sum_{j=1}^{J} p_{m,p}^j \log_2 p_{m,p}^j \tag{3}$$

where $P$ is the total number of branches and $p_{m,p}^j$ is the proportion of the class $j$ on the branch $p$. $p_{m,p}^j$ is given by:

$$p_{m,p}^j = \frac{N_{m,p}^j}{N_{m,p}} \tag{4}$$

where $N_{m,p}$ is the number of instances that take the branch $p$ and $N_{m,p}^j$ is the number of instances that take the branch $p$ and belong to the class $j$. The split that can maximize $Entropy_m - Entropy_m^{'}$ is taken at the node $m$.

Let $\mathbf{x}_i$ indicate a vector of predictors for the instance $i$ ($i = 1, 2, ..., N$, where $N$ is the sample size), $y_i$ denote the category for the instance $i$. The algorithm for developing a classification tree is as follows:

Step 1. Grow a large tree structure based on collected $N$ samples and $M$ predictors. A recursive process is conducted by picking the best predictors from $\mathbf{x}_i$ to reduce the entropy.

Step 2. Prune the large tree to obtain subtrees $ST_k$ ($k = 1, 2, ..., K$, where $K$ is the total number of subtrees).

Step 3. Predict the category $\hat{y}_i$ of the instance $i$ using the subtrees $ST_k$ in a cross-validation setting. The accuracy of the subtrees $ST_k$ is $\sum_i^N c_i / N$; where $c_i = 1$ when $y_i = \hat{y}_i$, otherwise $c_i = 0$.

Step 4. Select the best tree model from the subtrees based on the prediction accuracy.

Despite its advantages, the classification tree is found to generate unstable predictions given certain perturbations (Breiman 1996). To improve stability, Breiman (2001) proposed the random forest method which constructs multiple classification trees by bootstrapping (i.e. random sampling with replacement) the samples and employing random feature selection. The random forest lets each individual tree vote for the predicted class and uses the majority vote as the final output. The structure of the random forest is demonstrated in Fig. 3. The algorithm for developing and evaluating a random forest is as follows:

Step 1. Create a training subset $b$ ( $b=1,2,...,B$ , where $B$ is the predefined number of trees) by bootstrapping $n$ samples from the whole training set with size $N$ .

Step 2. Select $m$ predictors at random from $M$ predictors collected.

Step 3. Grow a classification tree $T_b$ based on selected $n$ samples and $m$ predictors in Steps 1 and 2. Obtain the predicted categories $T_b(\mathbf{x_i})$ for each instance.

Step 4: Repeat Steps 1-3 for $B$ times.

Step 5: Predict the category $\hat{y}_i$ for the instance $i$ using the mode of the set $\{T_b(\mathbf{x_i}) \mid b=1,2,...,B\}$.

Step 6: The accuracy of the random forest is $\sum_{i}^{N} c_i / N$; where $c_i = 1$ when $y_i = \hat{y}_i$, otherwise $c_i = 0$.

The random forest has been widely used in natural disaster management recently (Guikema et al. 2014; Nateghi et al. 2014; Staid et al. 2014; Wanik et al. 2015). Via selecting samples and features randomly and integrating outcomes of individual trees, the random forest is more robust with respect to noises. This noise robustness is essential in cell-based projection of evacuation zones in the presence of noisy data.

<Insert Figure Here>

**Fig. 3.** A structure demonstration of the random forest model

**Model Assessment**

Classification accuracy is widely used as a statistical measure of the extent to which the proposed classification tree and random forest perform. The accuracy can be simply computed by using the number of correctly classified instances divided by the total number of instances. However, using the accuracy as the only performance indicator can be misleading. For example, in the case there is a large class imbalance, a model which always predicts the majority class can achieve a high classification accuracy, but is not useful in the problem domain.

As an alternative to accuracy, Kappa statistic corrects for the potential biases caused by class imbalance. Kappa statistic is computed based on the difference between the observed agreement and the expected agreement obtained by random guess (Viera and Garrett 2005):

$$K = \frac{P_0 - P_c}{1 - P_c} \tag{5}$$

where $P_0$ is the proportion of observed agreements and $P_c$ is the proportion of agreements expected by chance. The Kappa statistic lie on a -1 to 1 scale, where 1 is the best agreement, 0 is what would be expected by chance and -1 is the worst agreement. According to Landis and Koch (1977), the magnitude of the Kappa statistic can be interpreted as: -1~0 = poor, 0.01~0.20 = slight, 0.21~0.40 = fair, 0.41~0.60 = moderate, 0.61~0.80 = substantial, and 0.81~1 = almost perfect.

To compare the predictive performance of different algorithms, a ten-fold cross-validation was performed in this study. The total dataset was split into 10 subsets randomly, and each of them was repeatedly left out as the validation set while the rest was used for training. The final accuracy and Kappa statistic were the combinations of outcomes when using each validation set for model assessment. The cross-validation can properly address the over-fitting issues.

**MODELING RESULTS**

The proposed classification tree and random forest were used to estimate evacuation zone categories based on the geographic features, evacuation mobility and demo-economic features. Open source software, Weka, was used to estimate the classification trees and random forests (Hall et al. 2009). A ten-folder cross-validation was performed to obtain accuracies and Kappa statistics. The selection of parameters in the classification tree and the random forest can have impacts on model outcomes. We tested a variety of parameter sets and selected the best combination based on model performance and convergence time. The parameters selected are summarized in Table 2.

Performance measures of the classification tree and the random forest are reported in Table 3. For comparison purpose, the performance measures of other commonly used machine learning methods including the logistic regression (Hosmer Jr and Lemeshow 2004), the support vector machine (SVM) (Cortes and Vapnik 1995) and the neural network (Hagan et al. 1996) are also presented. According to Table 3, both the classification tree and the random forest can result in higher accuracies than other machine learning methods and "almost perfect" Kappa statistics which are greater than 0.8. When comparing their performance, the random forest can yield higher accuracy than that of the classification tree (95.69% vs 91.95%). In addition, the higher value of Kappa statistic of the random forest provides additional evidence that the random forest has a better predictive performance.

To have a detailed evaluation of the predictive performance, the confusion matrices of the classification tree and the random forest are reported in Table 4 (a) and (b), respectively. For each zone category, the random forest results in more correctly classified instances than the classification tree does. For example, the random forest identifies 1,880 cells in the E1 zone correctly, which is greater than the number 1,745 by using the classification tree. Additionally, according to Table 4 (a), the random forest can output a really accurate prediction for each zone category. Only 13 cells out of 1,988 in E1 zone with high risk are classified as belong to safe zone, and only 7 cells out of 13,823 in the safe zone are regarded to be in the risky E1 zone.

Regarding the better performance, the prediction outcomes of the random forest are visualized in the GIS map and compared with actual evacuation zones as presented in Fig. 4. It is found that the estimated evacuation zone division is quite similar to the actual one. It implies that the random forest succeeds in learning the potential pattern of delineating zones with different risk levels. However, it is likely that the same random forest developed for Manhattan couldn’t achieve the same prediction accuracy for other regions, since the relationship between zone categories and risk factors are location-specific. The effects of predictors such as the distance to the cost and average elevation on flooding risks can vary greatly when confronting totally different hydrogeological environments in other regions. It is highly recommended to re-estimate the random forest models to capture the local characteristics of other coastal regions vulnerable to hurricanes and future effects of climate change.

<Insert Figure Here>

**Fig. 4.** Current evacuation zones (left) and predicted evacuation zones using the random forest (right)

## PREDICTION OF FUTURE EVACUATION ZONES

The main climate change which would have a great impact on the evacuation zoning is the sea level rise. The propose method can be used to promptly predict evacuation zones under different scenarios of sea level rises. As an example, this paper uses the sea level projections of the work reported in Zhang et al. (2014), which is a part of the New York State Resiliency Institute for Storms & Emergencies (NYRISE) project. In their study, two greenhouse gas emission scenarios are used to predict future sea level rise including the Representative Concentration Pathway (RCP) 4.5 (Thomson et al. 2011) and RCP 8.5 (Van Vuuren et al. 2011). In the RCP 4.5 scenario where countries work together to combat climate change, the climate radiative forcing to the atmosphere from anthropogenic emissions is 4.5 watts per square meter over the globe. The RCP 8.5 scenario assumes that little coordinated actions are made among countries, so that the climate radiative forcing to the atmosphere from anthropogenic emissions is as high as 8.5 watts per square meter over the globe.

Zhang et al. (2014) used a component-by-component analysis (Slangen et al. 2012) to project future sea level rises. The main components affecting sea level include global thermal expansion, local changes in ocean height, loss of ice from Greenland and Antarctic ice sheets, land water storage, etc. The future sea levels are forecasted under the "business as usual" emission scenario RCP 8.5. The upper 95% bounds of sea levels are estimated to be 0.92 m for the 2050s and 1.14 m for the 2090s. As a result of climate change, the terrain elevation above the sea level is expected to decrease. This will lead to a higher flooding risk and thus the evacuation zone categories need to be updated accordingly.

The change of demo-economic features is taken into consideration as well. Table 5 presents the population growth rate by age group. The projected growth rate for the whole population in Manhattan is 2.17% per ten years. Population decline is only observed for the age group 60~64. It is worth mentioning that the population over 85 have the highest growth rate 16.78%, which would increase the hurricane-related vulnerability. The total population and the populations in different age groups in the 2050s and the 2090s were predicted based on the assumption that the growth rates listed in Table 5 stay constant. Population below the poverty level, population not covered by health insurance, population with disability and population who are not proficient in English in the 2050s and the 2090s were predicted use the grow rate for the whole population in Manhattan (2.17%).

The proposed random forest is used to predict the evacuation zones for the 2050s and 2090s, based on the expected decrease in average elevation above the sea level, the changes in demo-economic features and the assumption that evacuation mobility is kept the same the future. The predicted future evacuation zones are presented in Fig. 5 Compared with the current zoning in Fig. 4, the areas with need of evacuation are expected to expand in the future. Despite the good performance of the random forest, it is inevitable to have prediction errors. A procedure to modify evacuation zones manually is suggested. Some principles are suggested to guide the modification of evacuation zones. For example, one type of evacuation zone may not be established within another. Also, some consideration should been given to the identifiable features of zoning (Wilmot and Meduri 2005).

<Insert Figure Here>

**Fig. 5.** Predicted evacuation zones for the 2050s (left) and the 2090s (right)

Comparisons of the current evacuation zones with the predicted evacuation zones for the 2050s and the 2090s are presented in Table 6. In the 2050s, the areas of the E1, E2 and E3 categories are expected to increase by 11.07% and 10.71% and 3.10%, respectively, compared with the current zone division; whereas the areas of the S category are expected to decrease by 5.33%. Similarly, in the 2090s, 15.95% more area of the E1 category, 4.94% more area of the E2 category, 5.83% more area of the E3 category and 6.09% less area of the S category are predicted. Projected evacuation zone divisions can be used by emergency managers to estimate evacuation demand in the future. Knowing the evacuation demand can be helpful in developing effective evacuation plans such as time to start evacuation and selection of evacuation routes, and in managing emergency resources such as determining the number of shelters, food and medicines provided to evacuees.

## SUMMARY AND CONCLUSIONS

This study develops a novel data-driven method to predict the division of future evacuation zones in the context of climate change, which is an essential input to estimate the resilience of transportation systems. The map of Manhattan was uniformly split into 45×45 $m^2$ grid cells as the basic geographical units of analysis. Evacuation zone category (E1, E2, E3 and S), geographical features (including average elevation above sea level and distance to coast), evacuation mobility (including distance to the nearest evacuation center, distance to the nearest subway station, distance to the nearest bus stop and distance to the nearest expressway), and demo-economic features (including total population, population below the poverty level, and population with disability) in the current year were captured for each cell. The future sea level rises estimated by Zhang et al. (2014) were used as an example to predict future evacuation zones. As a result of sea level rises, the average elevation above sea level is predicted to decrease and storm-related risk for the same region is likely to be higher in the future. Various machine learning methods were trained to relate cell-specific features with current zone categories which could reflect the risk levels during storms. Ten-fold cross-validation was used to evaluate model performance and it was found that the random forest outperformed the others in term of the accuracy and Kappa statistic. The random forest was used to predict the delineation of evacuation zones in the 2050s and 2090s, based on the predicted sea level rises and changes of demo-economic features. Compared with the current zoning, the areas with need of evacuation are expected to expand in the future.

A practical usage of our integrated methodology is that it combines the zoning model with the climate model to determine the change in evacuation zones in response to climate variability. The proposed data-driven method can be used to promptly estimate the evacuation zones under different sea level rise scenarios, without running storm surge simulations which are generally time-consuming and costly. Transportation system resilience in the context of climate change can be estimated based on the projected zonings under different scenarios. The proposed method can support decision-making in the evacuation planning and the management of emergency resources. For example, if the demand of evacuees increases dramatically in scenarios with sea level rises, it could take longer time to evacuee the residents prone to the hurricane-related risks, and thus the evacuation process should be started earlier. Also, the number of shelters, the amount of food and medicine stocked in evacuation centers are closely related to the demand of evacuees predicted. Thus, our results in this paper can be used to develop various realistic planning and training scenarios that reflect the impact of the predicted changes of evacuation zoning.

Despite the great performance of the random forest, domain experts are still needed to make the final decision about the size and type of evacuation zones. But we hope that the methodology proposed in this paper will provide them with additional insights. For future work, the study area will be expanded from Manhattan to the whole New York metropolitan area. An estimation of the number of residents to be evacuated in a larger region can be obtained. Additional work is needed to predict the future variation of evacuation mobility and demo-economic features, since they are closely related to the division of evacuation zones. Travel time could be used instead of travel distance as the metrics to represent evacuation mobility. In addition, evacuation simulation under different sea level rise scenarios will be conducted and level of services under those scenarios will be estimated to assess the resilience of transportation systems.

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**Table 1.** Descriptive Statistics of Predictors (N = 25,440 Grid Cells)

| Predictor | Mean | S.D. |
|---|---|---|
| **Geographic feature** | | |
| Average elevation above sea level (m) | 15.99 | 13.84 |
| Distance to coast (m) | 762.46 | 464.84 |
| **Evacuation mobility** | | |
| Distance to the nearest evacuation center (m) | 1014.34 | 519.64 |
| Distance to the nearest subway station (m) | 352.19 | 222.05 |
| Distance to the nearest bus stop (m) | 104.86 | 91.50 |
| Distance to the nearest expressway (m) | 565.47 | 434.10 |
| **Demo-economic feature** | | |
| Total population | 42.78 | 31.43 |
| Population not covered by health insurance | 6.54 | 6.82 |
| Population below the poverty level | 8.11 | 10.22 |
| Population with disability | 6.00 | 3.84 |
| Population who are not proficient in English | 9.60 | 13.81 |
| Population aged 0-4 | 2.94 | 2.47 |
| Population aged 5-9 | 1.85 | 1.68 |
| Population aged 10-14 | 2.68 | 2.64 |
| Population aged 60-64 | 3.24 | 2.56 |
| Population aged 65-74 | 4.40 | 3.52 |
| Population aged 75-84 | 2.59 | 2.42 |
| Population aged 85 and over | 1.17 | 1.25 |

Note: All the demo-economic features are indicating the number of people in specific groups.

**Table 2.** Parameter Selection for the Classification Tree and the Random Forest

| Classification Tree | Random Forest |
|---|---|
| ○ Prune trees: true<br>○ Confidence factor for pruning: 0.25<br>○ Maximum depth of the tree: unlimited<br>○ Minimum number of instances per leaf: 10 | ○ Maximum depth of the tree: unlimited<br>○ Number of features randomly selected: log(M)+1, where M is the total predictor number<br>○ Number of trees: 60 |

**Table 3.** Performance Measures of the Classification Tree and the Random Forest

| | Logistic Regression | SVM | Neural Network | Classification Tree | Random Forest |
|---|---|---|---|---|---|
| Correctly classified instances | 21582 | 21881 | 22784 | 23392 | 24342 |
| Incorrectly classified instances | 3858 | 3559 | 2656 | 2048 | 1098 |
| Total number of instances | 25440 | 25440 | 25440 | 25440 | 25440 |
| Accuracy | 84.83% | 86.01% | 89.56% | 91.95% | 95.69% |
| Kappa statistic | 0.7537 | 0.7724 | 0.8292 | 0.8694 | 0.9299 |

**Table 4.** Confusion Matrix of the Classification Tree (a) and the Random Forest (b)

(a)

| Decision Tree | | Classified as | | | | Total |
|---|---|---|---|---|---|---|
| | | E1 | E2 | E3 | S | |
| Actual zone category | E1 | 1,745 | 164 | 53 | 26 | 1,988 |
| | E2 | 180 | 2,436 | 339 | 43 | 2,998 |
| | E3 | 52 | 286 | 5,857 | 436 | 6,631 |
| | S | 33 | 47 | 389 | 13,354 | 13,823 |

(b)

| Random Forest | | Classified as | | | | Total |
|---|---|---|---|---|---|---|
| | | E1 | E2 | E3 | S | |
| Actual zone category | E1 | 1,880 | 76 | 19 | 13 | 1,988 |
| | E2 | 92 | 2,679 | 204 | 23 | 2,998 |
| | E3 | 12 | 191 | 6,180 | 248 | 6,631 |
| | S | 7 | 22 | 191 | 13,603 | 13,823 |

**Table 5.** Population Growth Rate by Age Group in Manhattan (Bloomberg and Burden 2013)

| Age Group | Population in 2010 | Predicted Population in 2040 | Growth Rate /10 years |
|---|---:|---:|---:|
| 0-4 | 76,579 | 76,687 | 0.05% |
| 5-9 | 61,323 | 66,801 | 2.89% |
| 10-14 | 58,229 | 63,630 | 3.00% |
| 60-64 | 85,574 | 82,682 | -1.14% |
| 65-74 | 115,369 | 131,655 | 4.50% |
| 75-84 | 68,397 | 97,394 | 12.50% |
| 85+ | 30,387 | 48,395 | 16.78% |
| Total Population | 1,585,873 | 1,691,617 | 2.17% |

**Table 6.** Comparisons of the Current Evacuation Zones with Predicted Evacuation Zones in the 2050s and the 2090s

| Zone Category | 2050s | | 2090s | |
|---|---|---|---|---|
| | Cell Number | Percentage Change | Cell Number | Percentage Change |
| E1 (current cell number=1,988) | 2,208 | 11.07% | 2,305 | 15.95% |
| E2 (current cell number=2,998) | 3,319 | 10.71% | 3,146 | 4.94% |
| E3 (current cell number=6,631) | 6,827 | 3.10% | 7,008 | 5.83% |
| S (current cell number=13,823) | 13,086 | -5.33% | 12,981 | -6.09% |

**Figure 1**

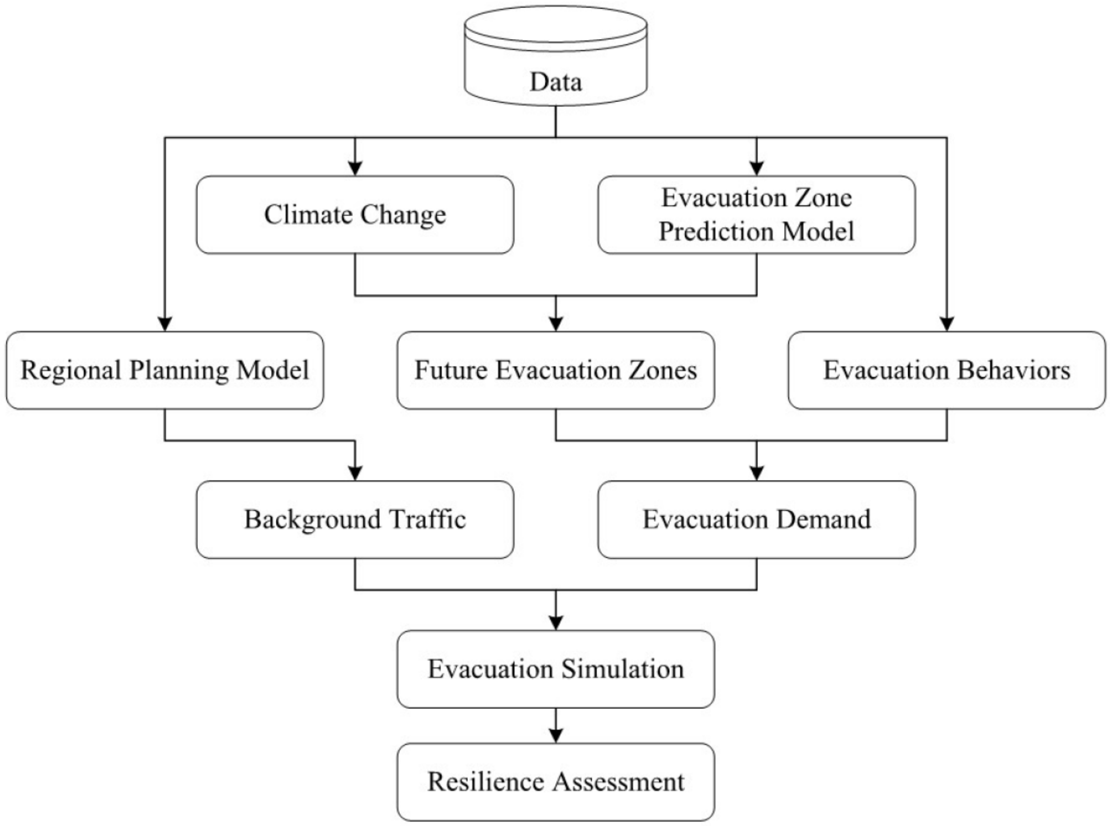
Data
Climate Change
Evacuation Zone
Prediction Model
Regional Planning Model
Future Evacuation Zones
Evacuation Behaviors
Background Traffic
Evacuation Demand
Evacuation Simulation
Resilience Assessment

**Figure 2**

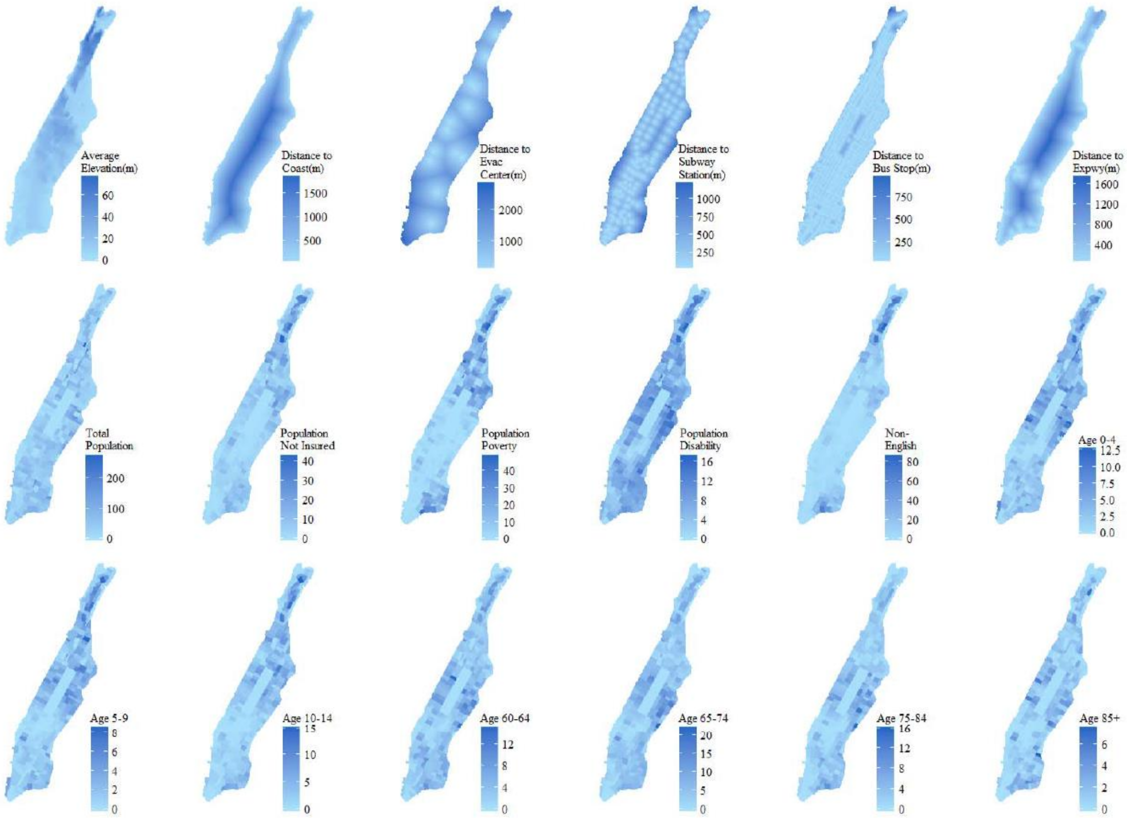
Average Elevation(m)
60
40
20
0
Distance to Coast(m)
1500
1000
500
Distance to Evac Center(m)
2000
1000
Distance to Subway Station(m)
1000
750
500
250
Distance to Bus Stop(m)
750
500
250
Distance to Expwy(m)
1600
1200
800
400
Total Population
200
100
0
Population Not Insured
40
30
20
10
0
Population Poverty
40
30
20
10
0
Population Disability
16
12
8
4
0
Non-English
80
60
40
20
0
Age 0-4
12.5
10.0
7.5
5.0
2.5
0.0
Age 5-9
8
6
4
2
0
Age 10-14
15
10
5
0
Age 60-64
12
8
4
0
Age 65-74
20
15
10
5
0
Age 75-84
16
12
8
4
0
Age 85+
6
4
2
0

**Figure 3**

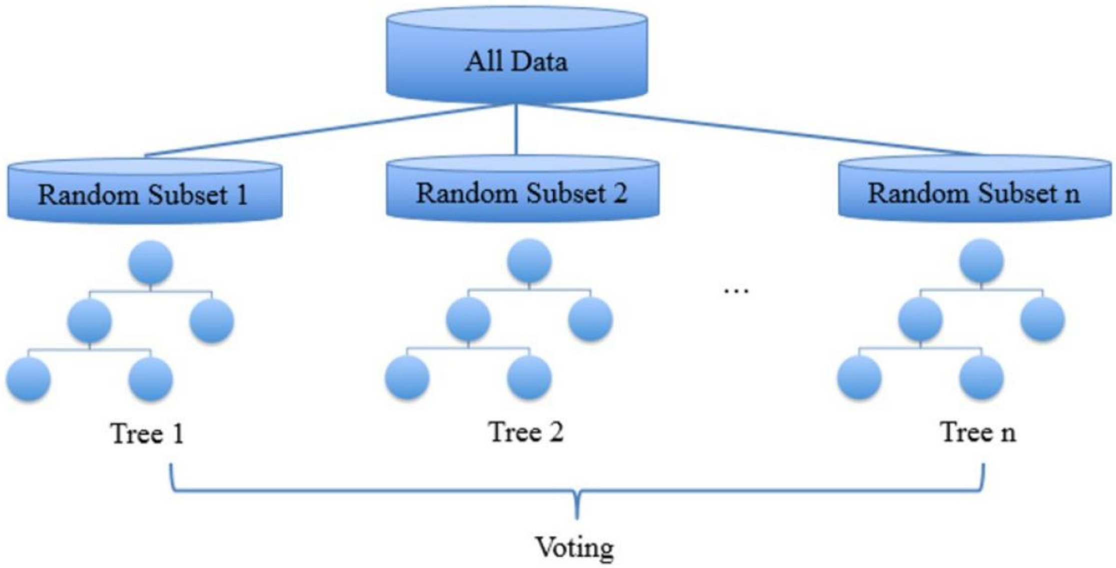
All Data
Random Subset 1
Random Subset 2
Random Subset n
...
Tree 1
Tree 2
Tree n
Voting

**Figure 4**

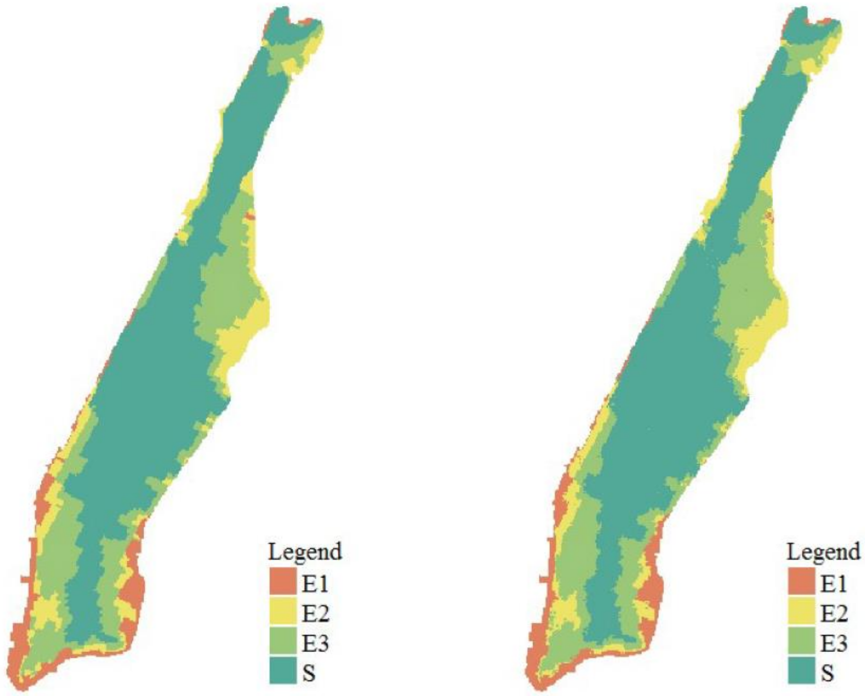

**Figure 5**