Transportation
https://doi.org/10.1007/s11116-021-10172-w

Evaluating impacts of coastal flooding on the transportation system using an activity-based travel demand model: a case study in Miami-Dade County, FL

Yu Han[1,3] · **Changjie Chen**[2] · **Zhong-Ren Peng**[1] · **Pallab Mozumder**[4]

Accepted: 11 January 2021

Abstract
Recent climatic disasters have shown the vulnerability of transportation infrastructures against natural hazards. To understand the risk of coastal hazards on urban travel activities, this study presents an activity-based modeling approach to evaluate the impacts of storm surge on the transportation network under sea-level rise in Miami-Dade County, FL. A Markov-Chain Monte Carlo (MCMC) based algorithm is applied to generate population attributes and travel diaries in the model simulation. Flooding scenarios in 2045 are developed based on different adaptation standards under the 100-year storm surge and population projections are from the land-use conflict identification strategy (LUCIS) model. Our analysis indicates that about 29.3% of the transportation infrastructure, including areas of the US No. 1 highway, roadways in the south and southwest of the county, and bridges connecting Miami Beach area, will be damaged under the storm surge when a low-level adaptation standard is chosen. However, the high-level adaptation standard will reduce the vulnerable infrastructures to 12.4%. Furthermore, the total increased travel time of the low-level adaptation standard could be as high as twice of that in the high-level adaptation standard during peak morning hours. Our model results also reveal that the average increased travel time due to future storm surge damage ranges between 14.2 and 62.8 min per trip.

Keywords Coastal flooding · Adaptation planning · Travel demands · Vulnerability · MATSim

✉ Zhong-Ren Peng
zpeng@ufl.edu

[1] International Center for Adaptation Planning and Design, School of Landscape Architecture and Design, College of Design, Construction, and Planning, University of Florida, P.O. Box 115706, Gainesville, FL 32611-5706, USA

[2] Florida Institute for Built Environment Resilience, University of Florida, P.O. Box 115701, Gainesville, FL 32611, USA

[3] Department of Earth and Environment, Institute of Environment, Florida International University, Miami, FL 33199, USA

[4] Department of Earth and Environment and Department of Economics, Institute of Environment, Florida International University, Miami, FL 33199, USA

Published online: 28 January 2021

Introduction

Recent global climatic disasters have shown clearly the need to enhance transportation resilience against sea-level rise (SLR) and storm surges (Kaufman et al. 2012). Although transportation infrastructure has been planned and maintained to provide conveyance of stormwater runoff through the roadway system, strong evidence shows that storm surges are occurring more frequently (Knutson et al. 2010; McCuen et al. 2002). Disruptions of passengers' travel activities could be significant if the road system is damaged over a long time period and less alternative routes are available to reach destinations. Therefore, It is crucial for transportation agencies to maintain a well-functioned transportation system under future weather conditions (Horner and Widener 2011).

Climate experts have predicted a continued rise in global mean sea level before 2100 (Parris et al. 2012). The Transportation Research Board (TRB) also suggest that transportation planning should be risk-based, and adaptation standards need to be evaluated regularly to incorporate climate change impacts (National Research Council 2008; National Academies of Sciences 2016). Currently, the FHWA uses frequency analysis, peak discharge estimation, and hydrograph analysis in the planning and design of stormwater management (FHWA 2017). However, due to the uncertain information of climate-related impacts on transportation systems and the tradeoff between the long-term and short-term planning goals, adaptation planning on transportation systems needs to accurately translate climate risk to local levels and assess systemwide vulnerability under these challenges.

A variety of transportation studies have focused on the vulnerability and accessibility reduction of the road network by comparing regional impacts of natural hazards before and after the failure of critical transportation infrastructure (Chang and Nojima 2001; Dalziell and Nicholson 2001). Lu and Peng (2011) applied a network-based approach to measuring accessibility reduction under SLR. An accessibility index was proposed to measure impacts of SLR on the transportation system. Similarly, Testa et al. (2015) examined the vulnerability of transport networks under extreme climatic weather events by measuring the topographic graph properties of a damaged network. Pregnolato et al. (2016) developed an integrated network-based framework to measure flood impacts on the transport network that relied on an interconnected road network and hazards map of Newcastle, UK. The network-based approaches focus on the topographical interactions of the road network, the failure of one link on the network will not affect travel speed and volume on other links, which is not likely to happen in reality (Cui and Levinson 2018). To improve accessibility measurement, Chen et al. (2015) proposed an improved accessibility index to measure transportation vulnerability based on the Florida Standard Urban Transportation Model Structure (FSUTMS). The FSUTMS provides a regional planning model in Florida based on the traditional four-step modeling to simulate travel demands. Although the FSUTMS has the advantage to capture regional travel patterns, it aggregates travel activities at traffic analysis zones (TAZ), which fails to capture activity disruptions of travelers on transportation systems (Taylor et al. 2006).

Different from traditional approaches, activity-based models (ABM) offers the flexibility to evaluate the impacts of environmental changes and transportation policies by capturing the travel behaviors of individuals (Castiglione et al. 2015). ABM can capture the travel demand shifts and improve the understanding of travel decisions in transportation assessment (Lyons and Marsden 2019). It has been applied to evaluate emerging travel demands, travel time, and travel decisions of travelers under emergency conditions (Chen et al. 2006; Yin et al. 2014).

To better evaluate disruptions of travel activities on the transportation system under future storm surge and facilitate adaptation planning on the transportation system, this paper calibrates an activity-based travel demand model and evaluates impacts of storm surges on daily travel activities of Miami-Dade County. The developed approach could illustrate the potential flood damage, affected population, and corresponding activity disruptions on the transport network. Compared to previous studies, this study aims to provide a policy analysis tool to improve the data application in transportation planning under uncertain climate-related impacts. This paper integrates multiple data sources to simulate travel diaries of residents and applies the Markov Chain Monte Carlo (MCMC) sampling algorithm to solve the challenge of capturing local travel characteristics. The developed scenarios incorporate the uncertainty of population projections. To improve model accuracy in capturing future population patterns, the developed activity-based travel demand model is integrated with a calibrated land-use simulation model to project distributions of population growth.

The remainder of this paper is divided into four sections. Section two provides a literature review on ABM applications. Section three presents the data collection and methodology in detail. Section four introduces an overview of the study area. Section five discusses the base model results, scenario results, and network vulnerability. Section six summarizes the paper with a brief discussion, conclusion, and future research directions.

Literature review

As one of the most popular ABMs, MATSim is a computational-based traffic simulation model that aims to optimize individual trip plans on the road system (Horni et al. 2016). MATSim framework includes three modules in the simulation: execution module, scoring module, and re-planning module. The execution module processes daily trip plans of the population, the scoring module measures the performance of each agent based on the utility function, and the re-planning module adjusts travel plans based on the evaluated scores (Zhuge et al. 2019). MATSim has been applied in evaluating emerging transportation technologies in travel mobility and population exposure to air pollutants from vehicles on roads (Eluru and Choudhury 2019; Hatzopoulou et al. 2011). Due to the activity-based trip assignment feature, MATSim can incorporate the randomness of individual travel behaviors in transportation policy evaluation. For example, Kaddoura et al. (2015) used MATSim to optimize public transportation fares and headways. Bassolas et al. (2019) applied MATSim to evaluate cordon toll policies by using mobile phone records to replace the travel survey in constructing activity diaries.

Population synthesis is one of the essential steps in ABM to generate travelers. Traditional fitting approaches have limitations in terms of efficiency and accuracy, various algorithms have been proposed to improve these limitations (Auld et al. 2009; Barthelemy and Toint 2013; Pritchard and Miller 2012). More recently, simulation-based approaches have been increasingly applied in population synthesis (Geard et al. 2013). The simulation-based population synthesis is able to traverse through the entire population attribute space based on the joint probability distributions. Farooq et al. (2013) presented a MCMC based approach, Gibbs sampler, to generate the joint distribution of households' attributes. Saadi et al. (2016) and Allahviranloo and Recker (2013) applied the Hidden Markov Model (HMM) to generate attributes of travelers. To estimate discrete HMM latent states, likelihood calculation could be implemented either using the direct filtering summations or using MCMC (Turek et al. 2016).

The assessment of flooding risk on the transportation network requires an explicit representation of the local flood risk, affected population, and the corresponding activity disruptions on the transport network (Dawson et al. 2016). To improve resilience in transportation planning, transportation models need to examine plausible future scenarios from a long-term perspective. Although existing MATSim studies reveal travel pattern changes under urban management policies, limited studies have integrated impacts of urban environmental changes on transportation system. To bridge the gap between activity-based travel demand model and land-use change models, Ziemke et al. (2016) integrated MATSim with an microscopic land-use change model to simulate large scale travel activities in the state of Maryland of the US. Saadi et al. (2018a) combined MATSim with a subgrid hydraulic model to project future urban trajectories with flood mitigation. Zhuge et al. (2018) develop a virtual land-use and transport model using MATSim to generate dynamic travel activities in Beijing.

Data and methods

Data collection

We investigate impacts of coastal flooding on the transportation system of Miami-Dade County relying on six types of dataset: the transportation network data from the Southeast Florida Regional Planning Model (SFRPM), the high resolution of DEM data and storm surge data from the National Oceanic and Atmospheric Administration (NOAA), the census data and parcel data from the Florida Geographic Data Library (FGDL), and the South Florida household travel survey from Florida Department of Transportation (FDOT). We listed all data sources in Table 1.

The transportation network data includes important road information about lane numbers, direction, road speed, and capacity, etc., which serves as an important data source to construct the urban transport system. To develop transportation system after storm surges, we applied the land elevation data, the 100-year storm surge data, and a SLR projection to construct the flood inundation model on the transportation system. The high resolution of land elevation data has a resolution higher than 30 cm with a confidence interval higher than 90% (Lu et al. 2015).

The census data contains the household's information on the census tract level. The parcel data includes information about individual buildings in the study area. The census data and the parcel data are used to generate population distributions in 2045. The South Florida

Table 1 Model adaptation scenario description

Scenario	Description	Adaptation storm surge height (m)	Adaptation flood return period
Scenario 1	The low adapted network	3.57	50-year
Scenario 2	The moderate adapted network	4.05	100-year
Scenario 3	The high adapted network	4.94	500-year

household travel survey data contains household level travel characteristics in Miami-Dade County. The dataset includes 9,449 individual trips in the Miami-Dade area. Every single trip includes information on trip begin time, origin and destination locations, previous trip type, next trip type, and socioeconomic attributes of households.

Model overview

MATSim uses a co-evolutionary process to optimize traffic conditions on road networks and travel patterns of travelers (Horni et al. 2016). Road network and population files are two major inputs. The road network file includes road segment attributes, such as road capacity, post speed, road direction, etc. The population file contains the detailed time-of-day travel information for each traveler. In this study, we first built a base model based on the 2018 population and transportation network. To evaluate storm surge impacts on the transportation network, we further developed future flooding and population growth scenarios.

Figure 1 shows an overview of model development. The transport system under flood damage is processed based on the transportation network file and flood inundation maps. Depending on the flooding scenario, we first identify flooded roadways on the transport network and then update free-flow speeds of damaged roads. The population is generated based on the travel survey data and projected population in 2045. To simulate future

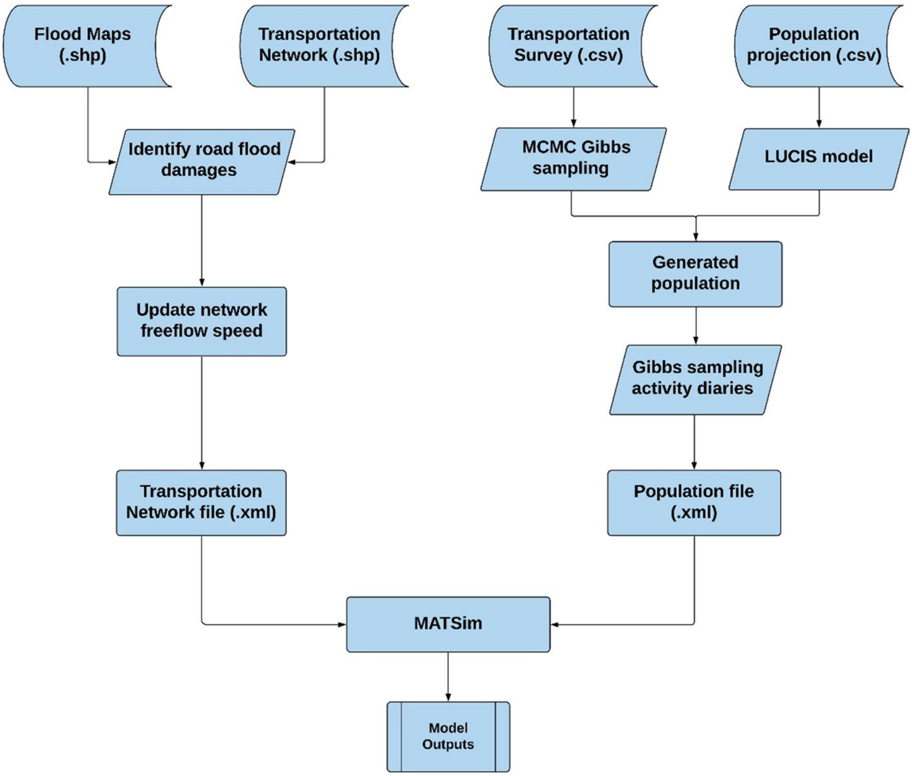


Fig. 1 An overall framework of model development

population patterns, the land-use conflict identification strategy (LUCIS) model is applied to simulate future population distribution in the area. A MCMC algorithm, Gibbs sampler, is adopted to estimate population socioeconomic attributes. Based on the generated population, we continue use Gibbs sampler to simulate population travel diaries. The updated transportation file and the population file are then transformed as model inputs. Our analysis is based on converged model outputs in MATSim.

Network and adaptation scenarios

Hurricane generated storm surges cause inundations on the transportation network. Since coastal transportation systems are designed to withstand from storm surge, we considered hydraulic adaptation measures on the transportation network. Currently, the NOAA, U.S. Army Corps of Engineers (USACE) and FDOT use peak storm surge height at return intervals of 50 years, 100 years, and 500 years to design hydraulic engineering on Florida's highway system (FHWA 2017; USACE 2017). The designed hydraulic structures, such as drainage systems and pumps, provide proper adaptation capacity to mitigate flood risk on the roadway system (FHWA 2017). We found the designed peak storm surge heights with a return period of 50, 100, and 500 years in Miami-Dade County are 3.57 m, 4.05 m, and 4.94 m, respectively (FDOT 2019). Although these three hydraulic standards correspond to three return periods, flood heights in each return period could still be higher than the designed peak flood height in risk-prone areas. Since the 100-year storm surge inundation map is used to determine local flood risk by the Federal Emergency Management Agency (FEMA), we use the 100-year storm surge to measure the resilience of the transportation network (FEMA 2020). Consequently, we consider these three levels of adaptation standards as flood adaptation scenarios, as shown in Table 2. Scenario 1 is the low adapted network with adaptation for the 3.57 m peak storm surge height, scenario 2 is the moderate adapted network with adaptation for the 4.05 m peak storm surge height, and scenario 3 is the high adapted network with adaptation for the 4.94 m peak storm surge height.

We use the 100-year storm surge flooding map from NOAA's SLOSH model to estimate the damage of flooding on the transportation network. To estimate the impacts of flood damage on the transportation network, the ground elevation is used to represent road elevations, then the flood height is estimated on the transportation network based on the local sea level rise (SLR) projection. To incorporate the effects of SLR, we choose the NOAA sea-level trends projection in Miami-Dade, which is based on the historical sea level data since 1920 in Miami Beach (Parris et al. 2012). A SLR of 0.11 m in 2045 with a 95%

Table 2 Model data description

Input data	Description	Resolution	Source
Transportation Network	Transportation network in Miami-Dade County with nodes and links	–	SFRPM
DEM data	The high resolution of LiDAR elevation data	2 m	NOAA
storm surge data	100-year storm surge maps	30 m	NOAA
census data	US Census geographic data of Bay County in 2018	Census tracts level	FGDL
parcel data	The cadastral parcel data in 2018	Parcel level	FGDL
Travel survey	the South Florida household travel survey	–	FDOT

confidence interval is projected to the current sea level (USACE 2017). The flood height is updated accordingly by incorporating the SLR height.

Afterward, we calculate the flood height above the designed peak storm surge height, and estimate the reduced free-flow travel speed on the transportation system. The disrupted free-flow speed of a road segment is estimated based on an empirical inundation-travel speed function (Pregnolato et al. 2017), where the travel speed will decrease to 0 when the flood height is above 0.3 m.

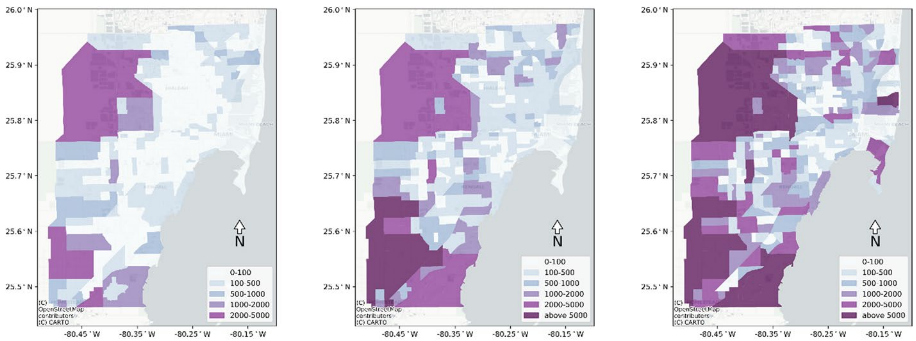
Population synthesis

The population synthesis generates a combination of micro attributes of households based on the household travel survey. The real population is seldom used in MATSim simulation due to the extremely high computational burden (Saadi et al. 2018b). In this study, we build the travel demand model by simulating 5% of populations in each scenario. Correspondingly, the scaling parameter is set up as 0.05 to simulate traffic flow in real conditions.

The population files are generated from census tracts. We use the census tract data in 2018 to simulate the population file in the base model. As a result, a total of 44,247 households is generated. For population files in 2045, we generate the total number of agents based on projected populations from the Bureau of Economic and Business Research (BEBR) and the land-use conflict identification strategy (LUCIS) model (Hart 2009).

We applied the LUCIS model to simulate future land-use change scenarios using the projected total population in 2045 by BEBR. The LUCIS model is a calibrated land-use change model in Florida by considering local building codes and land-use suitability. It has been deployed in the HiPerGator cloud computing environment at the University of Florida to simulate parcel-level land-use changes. There are three county population projections in the BEBR's annual report, the low, medium, and high population projections. The three population projections in 2045 are 2.97 million, 3.59 million, and 4.33 million, respectively. The medium county projection provides the most accurate forecasts of future population change, and the low and high projections indicate the uncertainty of population projections (BEBR 2019).

Three population growth scenarios are applied to simulate future population distributions, and populations are aggregated into census tracts for population synthesis. Figure 2



(a) Low population growth scenario **(b)** Medium population growth scenario **(c)** High population growth scenario

Fig. 2 The simulated population growth scenarios in census tracts from the LUCIS model shows the three simulated population growth scenarios in census tracts. Since coastal areas of the county have a high residential density, future population growth is more likely to happen in census tracts of the south and west of the county in all population growth scenarios. However, some of these areas, such as census tracts in the south and southwest of the county, are highly vulnerable to flooding events. Under the high population growth scenario, high population growth (above 5000) will happen in flood-prone areas in the south, southwest, and northeast of the county. Results in Fig. 2 indicate that, due to the SLR and increasing population exposure to hazards, future population growth may result in higher vulnerabilities of the transportation network in Miami-Dade County.

A total of five discrete attributes (household income, household size, number of children, number of available workers, and number of available vehicles) are simulated based on the household travel survey data. All attributes are classified into categorical variables in the population synthesis process based on the HMM. In the HMM, the states of the current attribute only depend on previous state observations (Saadi et al. 2016). The estimation of HMM could be achieved using Markov Chain Monte Carlo (MCMC) sampling (Turek et al. 2016). The probability to generate a random sequence can be expressed as:

$$P(\boldsymbol{\theta},\ \boldsymbol{X}|\boldsymbol{Y}) \propto P(\boldsymbol{\theta}) \times \prod_{k=1}^{N} P\left(X_k|\boldsymbol{\theta}\right) P\left(Y_k|\theta, X_k\right) \tag{1}$$

where $P(\boldsymbol{\theta},\ \boldsymbol{X}|\boldsymbol{Y})$ is the probability distribution of hidden states $\boldsymbol{X}$ with model parameters $\boldsymbol{\theta}$, and $\boldsymbol{Y}$ represents the observed sequence of hidden states. $P(\boldsymbol{\theta})$ represents probabilities of the model parameters. $P\left(X_k|\boldsymbol{\theta}\right)$ represents conditional probability of hidden state X_k on model parameters, $P\left(Y_k|\theta, X_k\right)$ is observational probabilities. X_k is the category of the kth hidden state, Y_k represents the category of the kth attribute in the observational space. In a hierarchical space, the MCMC algorithms, e.g. Gibbs sampling, based on Eq. (1) could be very inefficient. Instead, relying on the discrete structure of HMM, an alternative approach can be used to only estimate the posterior distribution of $\boldsymbol{\theta}$, as shown in Eq. (2).

$$P(\boldsymbol{\theta}|\boldsymbol{Y}) \propto P(\boldsymbol{\theta}) \times \prod_{k=1}^{N} P\left(Y_k|\theta\right) \tag{2}$$

The Eq. (2) uses filtering to estimate $P\left(Y_k|\theta\right)$ in the calculation of model likelihoods (Elliott et al. 2008). In the calculation of Eq. (2), Gibbs sampling could be used to simulate agents' attributes.

Travel dairy generation

The travel activity of residents, including the trip purpose information, the travel time-of-day information, and the origin–destination (O-D) information, are required to construct the population travel diary. In this study, we generate a travel activity plan for each traveler based on a Markov chain of trip activities. Six types of activities, including home, work, school, shop, leisure, and other activities, are included in the activity transition matrix. Since each trip plan represents a household's daily activity plan, in this study, we assume each daily trip plan starts from the home and ends at the home. Consequently, at least two trips are included in each daily travel plan. In addition, we further assume that the destination of each trip will become the origin of the next trip. We apply the Gibbs sampling to generate the activity type, trip begin time, and the destination of each trip. Consequently, marginal and conditional probability matrices are constructed to estimate activity type, the start time of activities, and the O-D information.

In this study, we build a total of 9 flooding scenarios in the year 2045 to evaluate the impacts of coastal storm surge on travel patterns of individuals. Nine cases are developed for the flooded transportation system with the low adapted network, the moderate adapted network, and the high adapted network under the three population growth scenarios. Each scenario is simulated with 100 iterations to have converged model results. Since the medium population growth scenario represents the most accurate population projections, we apply the medium population projection to evaluate our results and incorporate the low and high population growth scenarios as result uncertainties.

Overview of study area

As one of the low elevated areas on the southeast coast of the United States, over two thirds of the transportation system in Miami Dade County is now exposed to the risk of storm surge and king tides (Chen et al. 2015). During the most devastating 2003 Atlantic hurricane season, the direct economic cost of flooding on infrastructures and properties was over $100 billion, where Miami Dade County was one of the most damaged areas in the United States (Lawrence et al. 2005).

The flood issues during the hurricane season threatens the well-functioning of the transportation system and daily activities in local communities (Ezer and Atkinson 2014). Figure 3 shows the inundation of the category 4 storm surge in Miami-Dade County, which is equivalent to the storm surge with 100-year return period or higher (Keim et al. 2007). It can be seen that areas in the south, southwest, and northeast of the county is under the risk of inundation. The flood damage on the road network after the storm surge will disrupt travel activities and increase travel costs of residents. Therefore, a better understanding of flooding impacts of storm surge on the transportation network will benefit the long-term transportation planning and improve transportation resilience.

Results

Base model results

Our base model is simulated based on the 2018 census population and transportation network. Model results are compared with travel survey data for model evaluation. We built the training model with 70% of randomly selected data from the travel survey and validated results with the rest of the data.

Since the joint categorical distribution of households' attributes can accurately reflect model results, we evaluated our base model using the distributions of joint attributes in the base model and the travel survey. Figure 4 shows the fitness of joint distributions of simulated households' attributes. We use discrete numerical values to represent categories of each attribute. The values in Fig. 4 represent the products between two attributes. We fit a linear model between the simulated and the observed data. In general, the simulated

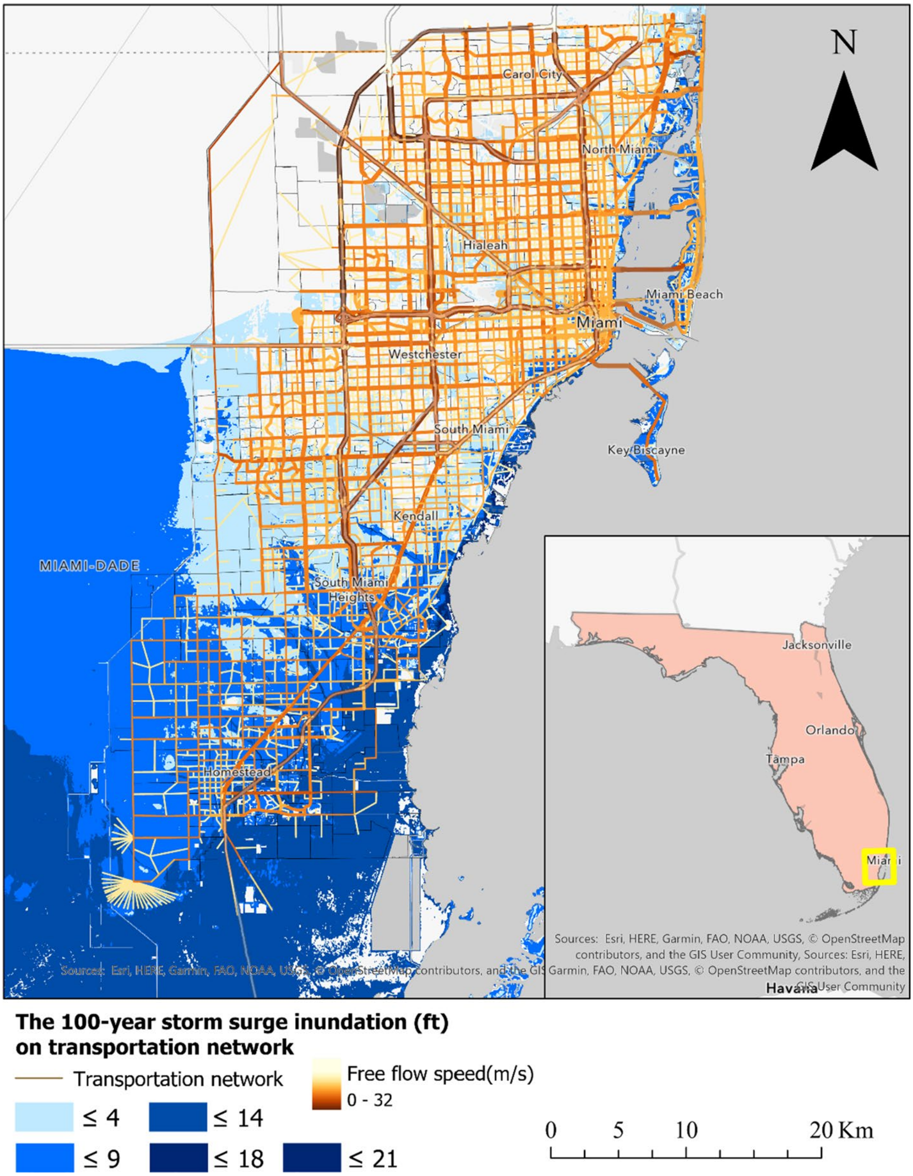


Fig. 3 The transportation system under flood inundation of the 100-year storm surge in Miami-Dade County

proportions of joint attributes in the base model are close to that in the household travel survey, and therefore, the slopes of the fitted models are all close to 1.

The joint distributions of agents' attributes can accurately reflect households' characteristics in the travel survey dataset. Due to the randomness of population synthesis and missing values in the survey data, small deviations exist in Fig. 4. Nevertheless, the

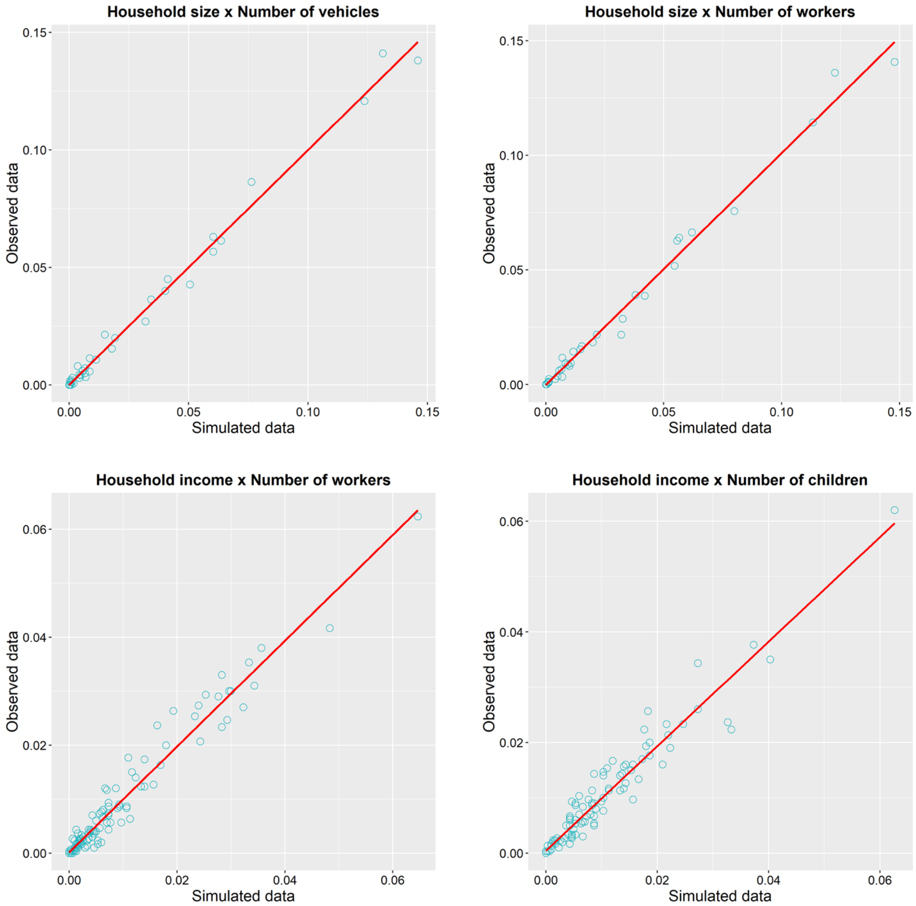
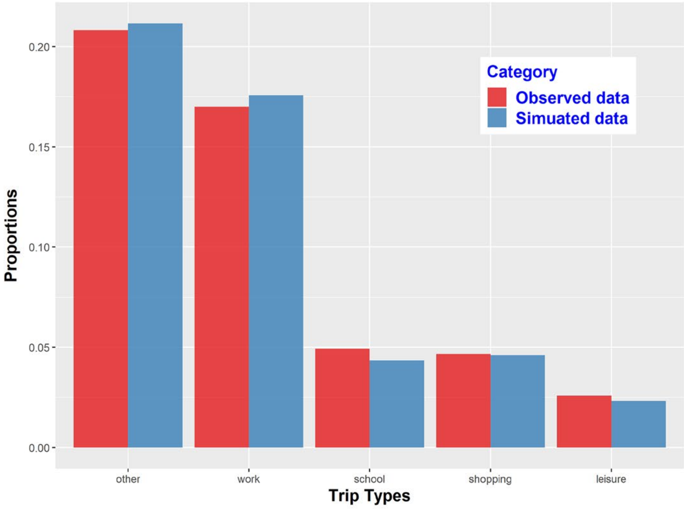


Fig. 4 Model validation of households' attributes between the model simulation and travel survey

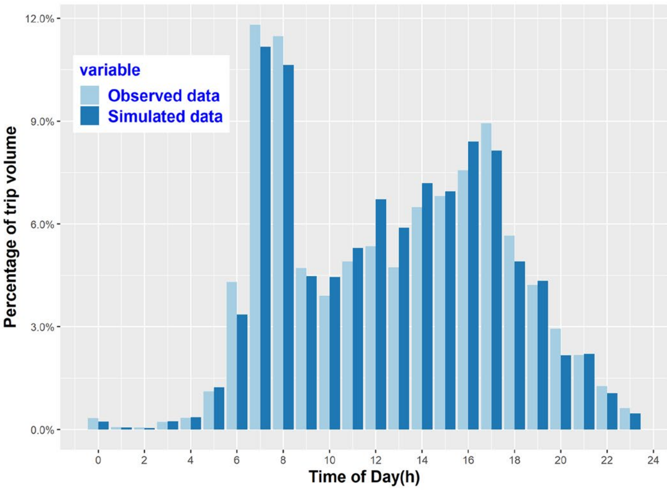
generated socio-economic attributes of households can accurately reflect travel characteristics in the study area. We then generated travel plans of agents based on the simulated socioeconomic attributes.

To better validate our model results, we classify individuals' travel activities into five categories of trip type (work, school, shop, leisure, and other). Since each simulated trip plan may include multiple travel activities, the classified activity type distribution can reflect results accuracy. We compared the simulated trip type distributions with the travel survey, as shown in Fig. 5a. Although small deviations exist in the model results, results in Fig. 5a show consistent trip type distributions between the simulated and observed travel activities. In Fig. 5a, the work and other activities account for the majority of traffic volume. The school and shopping activities take about 10% of the total trip volume.

We also show the percentage of time-of-day trip volume. Results in Fig. 5b indicate that the simulated time-of-day traffic volume follows the trip volume distribution in the travel survey. The time-of-day traffic volume distribution also indicates the time of traffic on the transportation system in Miami-Dade County. In general, there are few trips from 0:00 am to 4:00 am. Morning peak hours start from 7:00 am to 9:00 am, after which the trip volume



(a) Activity Type



(b) Time of day traffic volume

Fig. 5 Model fitness between the simulated and the observed marginal distribution in the base model

will gradually decrease until 12:00 pm. After 12:00 pm, the trip volume will gradually increase, and the evening peak hour starts from 04:00 pm to 06:00 pm. After 6:00 pm, the traffic volume will gradually decrease again.

We further use joint distributions of the simulated trip plans to validated model results. Figure 6 shows four model finesses of the joint distributions, including activity type and trip begin time, previous trip activity and next trip activity, household income and trip destination activity, and activity type and trip destination TAZ. The simulated activity type and trip begin time have high accuracy. Small deviations exist in other results, whilst the

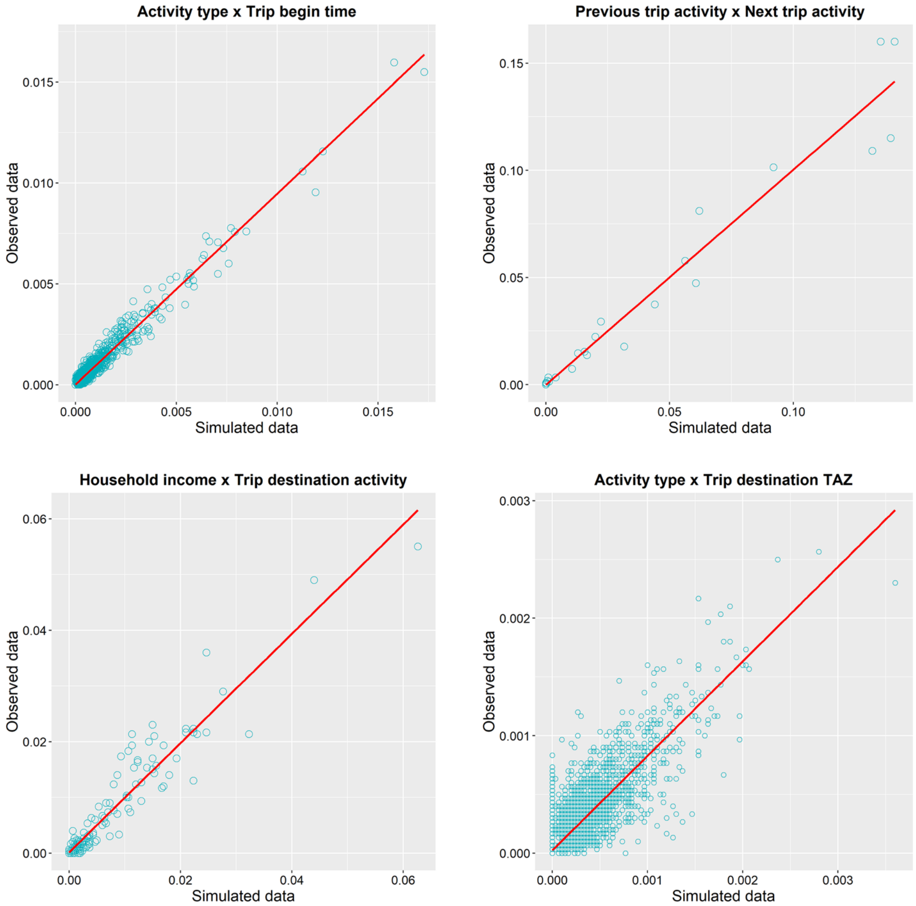


Fig. 6 Model validation between joint distributions of the simulated travel activities and travel survey

fitted slopes of linear models in Fig. 6 are close to 1, except for the model of activity type and trip destination TAZ. This could result from imperfect observations in the travel survey data and model assumptions. We assume each trip originates from home and the destinations are generated based on the O–D matrices. These assumptions could be inconsistent with the survey data, where trips can start from non-home locations, and activities are also affected by travel behaviors of travelers. Since the travel survey data provides discrete trip information, it cannot perfectly capture a combination of activities of travelers.

Results in Fig. 7 shows distributions of the simulated trip travel time based on activity types. It can be seen that our simulated travel time distributions have long-tail distribution characteristics. Most trips have travel time lower than 180 min, so we aggregate trip activities with travel time longer than 180 min. On average, the peak travel time interval is around 10–20 min. We use travel time distribution in the base model to compare with travel time distributions under flooding scenarios to show the potential impacts of coastal flooding on the transportation system.

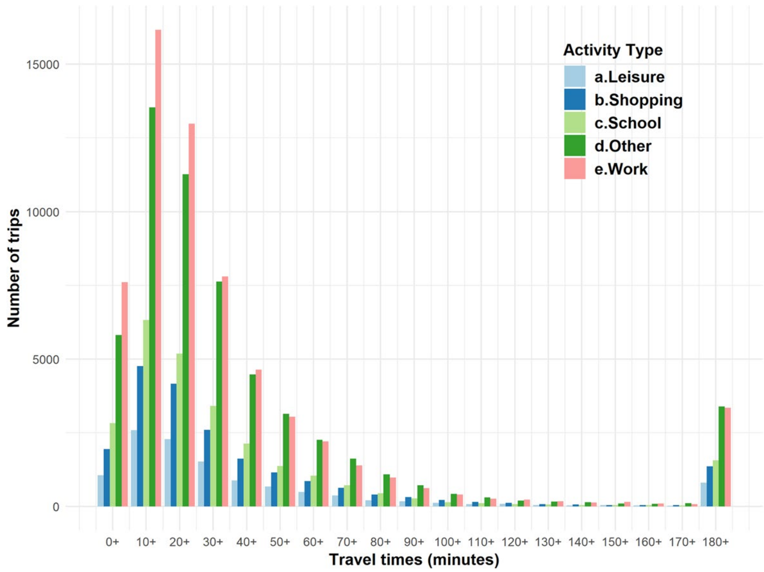


Fig. 7 The simulated number of trips based on travel time and activity type in the base scenario

Scenario results

We evaluated the simulated travel time distributions for each activity type under the 100-year storm surge flooding and the three adaptation scenarios. Since the low and high population projections represent uncertainties in population prediction, we incorporate results of the low the high population growth projections as error bars under each flooding scenario. The results in Fig. 8 show that the distributions of travel time will shift to the right under storm surge flooding, which indicates longer travel times for all activities. We show the average increased travel time for each type of activity under the medium population projection. Table 3 indicates that the average increased travel time on the transportation system under the 100-year storm surge ranges between 14.2 and 62.8 min per trip. For different activity types, school activities may be affected more seriously, where the average increased travel time ranges between 17.6 and 76.1 min. The work activity has increased travel times ranging between 12.8 and 65.6 min. Similarly, the increased travel time of other activities ranges between 14.7 and 67.6 min. These activities are more sensitive to damages on the transportation network. Although some activities, such as school activity, could be canceled in real life before and during hurricanes, our results present the worst case of daily traffic patterns after the 100-year storm surge in Miami-Dade County and also explain why these activities should be canceled during natural hazards.

Compare with Fig. 7, the distribution of travel time in Fig. 8 will shift more to the right when the transportation system is protected with a lower adaptation standard. When the network is adapted based on the 50-year storm surge, the distributions of travel time will become flatter. When the transportation network is protected with higher standards, coastal storm surge will have less impact on urban travel activities. On the other side, uncertainties of population projections will also impact the distributions of daily travel time under flooding scenarios, while the impacts are not as high as the chosen adaptation standard.

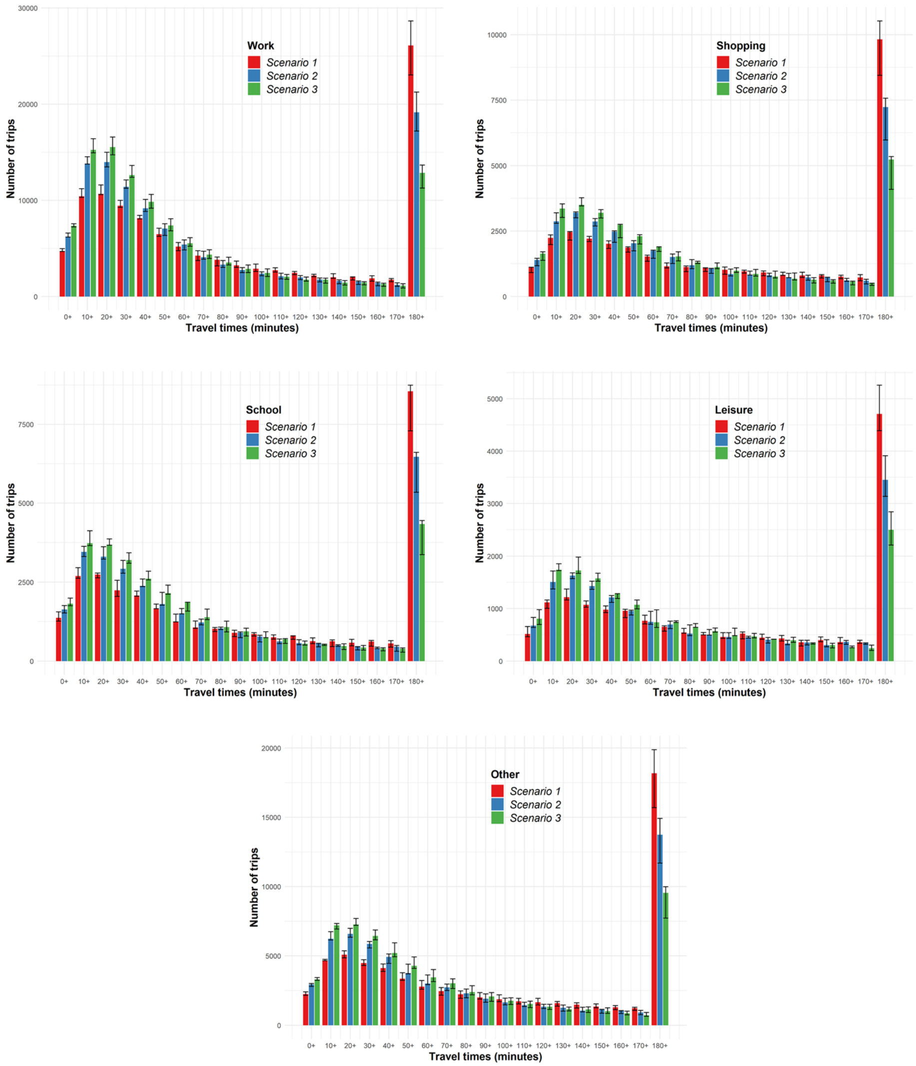


Fig. 8 The simulated travel time distributions under the 100-year storm surge flooding and adaptation scenarios in 2045

Table 3 The average increased travel time per trip based on activity types

Activity type	Low protected network (min)	Moderate protected network (min)	High protected network (min)
Leisure	56.6	33.7	12.5
Shopping	57.9	35.7	14.0
School	76.1	51.6	17.6
Work	65.6	40.5	12.8
Other	67.6	43.6	14.7
Total	62.8	40.4	14.2

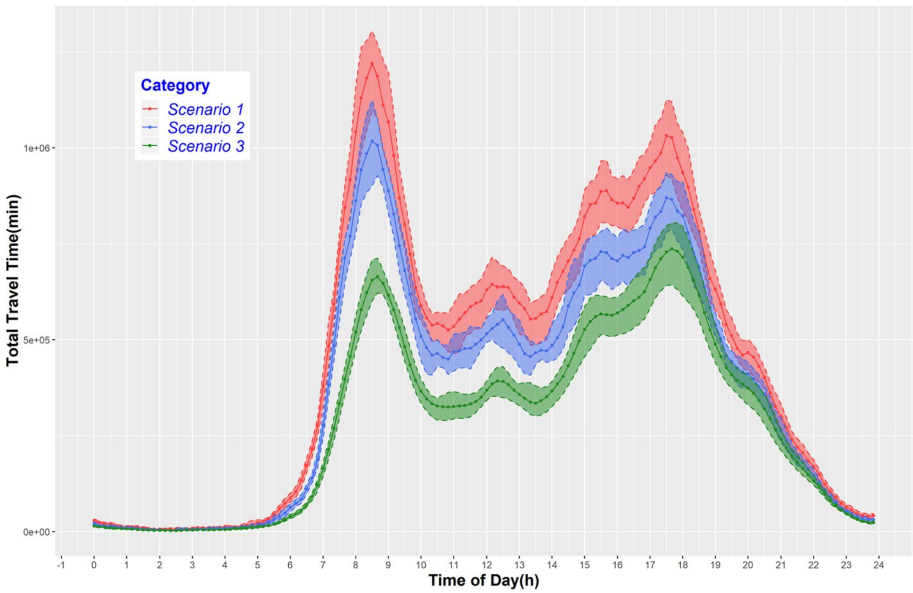


Fig. 9 Time-of-day total travel time under the 100-year storm surge flooding and adaptation scenarios in 2045

However, the impacts of population projections on the distributions of travel time could be amplified over twice under different adaptation standards.

We show total travel time on the flooded network under different adaptation scenarios based on the time-of-day, as shown in Fig. 9. We aggregate our results using a 10-min time window. The total travel time during the daytime traffic hours is between $2.6 \times 10^5 \sim 1.6 \times 10^6$ min. The uncertainties of total travel time under the time-of-day are estimated based on the low and high population projections. On average, both scenario 1 and scenario 2 have much higher total travel times. The total travel time in scenario 3 has about $\frac{1}{2}$ of that in scenario 1 during peak morning hours, which means a higher travel efficiency on the transportation network under the high adaptation standard. Our model results indicate a higher resilience of the scenario 3 under the 100-year flood damage. Furthermore, scenario 1 has high uncertainties of total travel time, which can be explained by the fact that population growth is more likely to appear in flood-prone areas in the south and southwest of the county.

The network vulnerability

We measured locations of vulnerable road segments after the storm surge in terms of total increased travel time based on the simulated travel patterns of agents, and results are shown in Fig. 10. We use the daily increased travel time of flood damage to show the vulnerability of road segments (Shen et al. 2016). To calculate the daily increased travel time of flood damage, we ran another three scenarios of the low, medium, and high population projections based on the unflooded network, we then aggregate total increased travel time on the transportation network. Although travel activities may not actually happen during flood

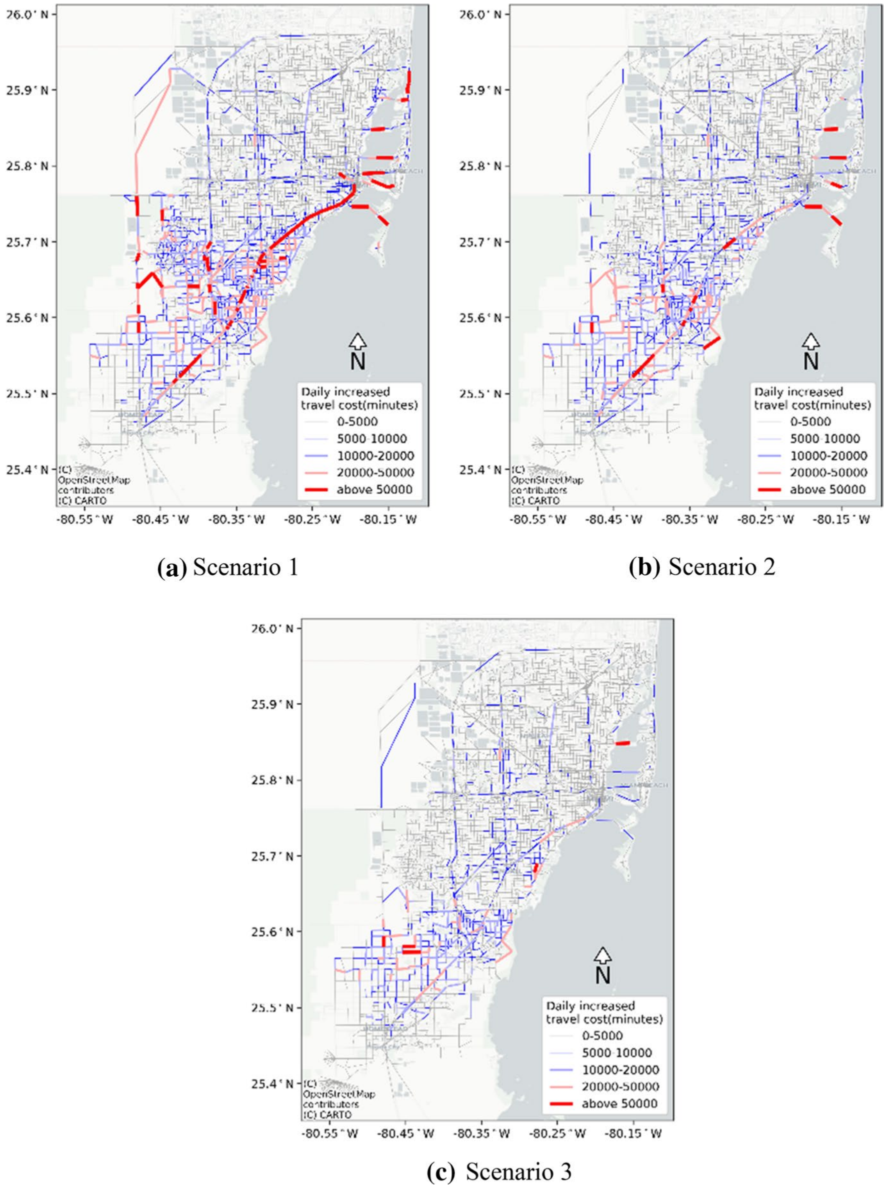


Fig. 10 The total daily increased travel time on the road network under the 100-year storm surge flooding and adaptation scenarios in 2045

periods, the inundated highway pavement could be permanently damaged under extreme hazards. Moreover, the increased travel time of flooding could identify the vulnerability of transportation infrastructure. Since the population projection errors have a small influence on final results, we show total travel costs on the transportation network under the medium population growth scenario.

When the network is protected with the low adaptation standard, the transportation system in Miami-Dade County could have a high risk of inundation. The US No. 1 highway, which is along the county's east coast from south to north, has the highest vulnerability to the 100-year storm surge. The total increased travel time on the US No. 1 highway is over 5000 min. Moreover, bridges connecting Miami Beach and Miami-Dade County also have the highest level of vulnerability after the 100-year storm surge damage. Parts of the road network in the south and west of the county also has the highest vulnerability due to low elevations. When the moderate level of flood protection criteria is chosen, some highly vulnerable road segments in the south and west are protected from flooding. Only areas in the south of the county, parts of the US No. 1 highway, and a few bridges and roads in the north of the county are still at high risk. When the road network is protected with the high adaptation standard, few roads in the south and east coast of the county are vulnerable to the 100-year flood damage. To adapt to climate change, a high adaptation standard for some vulnerable infrastructure, such as the US No. 1 highway and bridges connecting to Miami Beach, is crucial to reduce traffic disruptions after storm surge damage. In general, results in Fig. 10 illustrate vulnerable locations of the transportation system to storm surge events and also reveal the potential benefits of adaptation on the transportation system. In the transportation planning process, these results could be used as data applications to determine uncertain natural hazards impacts.

Discussion and conclusion

Adaptation planning has been discussed extensively on the local, regional, and state levels, while uncertain information about climate-related impacts restrains successful adaptation in transportation systems (Bedsworth and Hanak 2010). Our results show that future climate hazards can cause significant impacts on the transportation system in Miami-Dade County. These impacts will increasingly apparent in the southeast coasts of Florida (Wdowinski et al. 2016). The methodology developed in this study presents an alternative approach to evaluate systemwide impacts of storm surge and SLR on transportation systems, which could improve data application in local and state transportation plans.

To reduce uncertainties of climate impacts in transportation planning, coastal flooding on transportation systems would need to be evaluated to consider a full range of possible climate change impacts. Our base model is validated using travel survey data to reflect the average daily traffic patterns in the study area. The MCMC-based approach used in this study could accurately simulate households' attributes and travel characteristics. Although deviations exist between trip activity and destinations, the proposed methods could solve the challenge of capturing local travel characteristics. Our model scenario simulates the daily travel activities under the inundated transportation network based on the projected population and travel survey data. Since some activities could be canceled or changed before and after a short period of the coastal storm surge, our scenario results may not reflect dynamic travel activities before or during the 100-year storm surge event. However, considering the risk of transportation infrastructures under coastal hazards is increasing, the transportation system may fail to provide proper functionality for a long period after coastal storm surge events. Results in this study directly illustrate flood risk on the transportation system, which can provide data support for local adaptation planning to compare adaptation benefits. Our results indicate that the average increased travel time on the transportation system under the 100-year storm surge ranges between 14.2 and 62.8 min per trip. For different activity types, school activity may be affected more seriously, where the average increased travel time ranges between 17.6 and 76.1 min. Our scenario results also show potential benefits of the high adaptation standard in vulnerable areas of the county, including the US No. 1 highway, roadways in the south and southwest of the county, as well as bridges connecting Miami Beach and Miami-Dade County. On the other side, population growth could increase travel time on the transportation system. Compared to different adaptation scenarios, the uncertainty of population growth in 2045 could result in higher disruptions on the transportation system under the low protected network scenario. Since population growth is more likely to happen in the south and southwest of the county, this indicates that transportation planners need to upgrade adaptation standards in those risk-prone areas with high population growth in designing risk mitigation plans on the transportation system.

Our projected SLR belongs to the low category of SLR projection. Although it has a 95% confidence interval based on the local historical sea-level records, SLR is possible to increase more dramatically under higher greenhouse gas emissions and faster melting glaciers (Pachauri et al. 2014). Urban planners need to timely incorporate these changes in assessing potential climate risk and appropriate adaptive measures in transportation planning (Picketts et al. 2015). MATSim, as one of the promising activity-based modeling approaches, could facilitate this process in risk evaluation and adaptation decision-making in transportation planning.

To further improve capabilities of the developed model in flood risk management, some shortcomings need to be noticed and further improved. First, this study only considers the impacts of storm surge on vehicle travel demand. The impacts of climate change on other travel modes, such as bus and truck, are not considered in the current model. Future studies could incorporate more travel modes into the evaluation of flood impacts for different groups of travelers. Second, this study uses a data-driven approach to calibrate and validate population attributes and trip diaries. To better evaluate travel characteristics of travelers under coastal hazards, future studies could incorporate new data sources to capture impacts of coastal storm surge on travel demands in the trip generation process. Third, this study evaluates storm surge impacts based on the travel survey data. Since the state of Florida is proposing a voluntary property buyout program to phase out high-risk properties in flood zones, a planned retreat may happen in Miami-Dade County before 2045 (Siders 2019). Future studies may further explore the long-term impacts of local adaptation policies on travel demands in coastal areas through the integrated land-use transport model developed in this study.

Acknowledgements We acknowledge the support from Florida Department of Transportation (FDOT). We also acknowledge the support from the National Science Foundation [Award #1832693: CRISP 2.0 Type 2: Collaborative Research: Organizing Decentralized Resilience in Critical Interdependent-infrastructure Systems and Processes (ORDER-CRISP)]. Contents of this study are solely the responsibility of the authors and do not necessarily represent the official views of the National Science Foundation or FDOT.

Author contributions YH designed the study, conducted literature search and review, developed and calibrated the MATSim model and conducted scenario analysis. CC conducted the LUCIS model simulation and visualization. YH and CC wrote the manuscript. Z-RP and PM reviewed and revised the manuscript. All authors read and approve the manuscript.

Compliance with ethical standards

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

References

Allahviranloo, M., Recker, W.: Daily activity pattern recognition by using support vector machines with multiple classes. Transp. Res. Part B Methodol. **58**, 16–43 (2013). https://doi.org/10.1016/j.trb.2013.09.008

Auld, J.A., Mohammadian, A., Wies, K.: Population synthesis with subregion-level control variable aggregation. J. Transp. Eng. **135**(9), 632–639 (2009)

Barthelemy, J., Toint, P.L.: Synthetic population generation without a sample. Transp. Sci. **47**(2), 266–279 (2013). https://doi.org/10.1287/trsc.1120.0408

Bassolas, A., Ramasco, J.J., Herranz, R., Cantu-Ros, O.G.: Mobile phone records to feed activity-based travel demand models: MATSim for studying a cordon toll policy in Barcelona. Transp. Res. Part A Policy Pract. **121**, 56–74 (2019). https://doi.org/10.1016/j.tra.2018.12.024

BEBR: Population Data Archive-Florida Estimates of Population. https://www.bebr.ufl.edu/population/data (2019).

Bedsworth, L.W., Hanak, E.: Adaptation to climate change. J. Am. Plan. Assoc. **76**(4), 477–495 (2010). https://doi.org/10.1080/01944363.2010.502047

Castiglione, J., Bradley, M., Gliebe, J.: Activity-based travel demand models: A primer. In., vol. No. SHRP 2 Report S2-C46-RR-1 (2015)

Chang, S.E., Nojima, N.: Measuring post-disaster transportation system performance: the 1995 Kobe earthquake in comparative perspective. Transp. Res. Part A Policy Pract. **35**(6), 475–494 (2001). https://doi.org/10.1016/S0965-8564(00)00003-3

Chen, X.W., Meaker, J.W., Zhan, F.B.: Agent-based modeling and analysis of hurricane evacuation procedures for the Florida Keys. Nat. Hazards **38**(3), 321–338 (2006). https://doi.org/10.1007/s11069-005-0263-0

Chen, X.Z., Lu, Q.C., Pang, Z.R., Ash, J.E.: Analysis of transportation network vulnerability under flooding disasters. Transp. Res. Rec. **2532**, 37–44 (2015). https://doi.org/10.3141/2532-05

Cui, M., Levinson, D.J.T.: Accessibility analysis of risk severity. Transportation **45**(4), 1029–1050 (2018)

Dalziell, E., Nicholson, A.: Risk and impact of natural hazards on a road network. J. Transp. Eng. **127**(2), 159–166 (2001). https://doi.org/10.1061/(Asce)0733-947x(2001)127:2(159)

Dawson, D., Shaw, J., Roland Gehrels, W.: Sea-level rise impacts on transport infrastructure: the notorious case of the coastal railway line at Dawlish, England. J. Transp. Geogr. **51**, 97–109 (2016). https://doi.org/10.1016/j.jtrangeo.2015.11.009

Elliott, R.J., Aggoun, L., Moore, J.B.: Hidden Markov Models: Estimation and Control, vol. 29. Springer, Berlin (2008)

Eluru, N., Choudhury, C.F.: Impact of shared and autonomous vehicles on travel behavior. Transportation **46**(6), 1971–1974 (2019). https://doi.org/10.1007/s11116-019-10063-1

Ezer, T., Atkinson, L.P.: Accelerated flooding along the US East Coast: on the impact of sea-level rise, tides, storms, the Gulf Stream, and the North Atlantic Oscillations. Earth's Future **2**(8), 362–382 (2014)

Farooq, B., Bierlaire, M., Hurtubia, R., Flötteröd, G.: Simulation based population synthesis. Transp. Res. Part B Methodol. **58**, 243–263 (2013). https://doi.org/10.1016/j.trb.2013.09.012

FDOT: Roadway Design: Design Hurricane Surge Hydrographs. https://www.fdot.gov/roadway/drainage/dhsh.shtm (2019).

FEMA: National Flood Insurance Program: Flood Hazard Mapping. https://www.fema.gov/national-flood-insurance-program-flood-hazard-mapping (2020).

FHWA: Bridges & Structures: Hydraulic Engineering. https://www.fhwa.dot.gov/engineering/hydraulics/ (2017).

Geard, N., McCaw, J.M., Dorin, A., Korb, K.B., McVernon, J., Simulation, S.: Synthetic population dynamics: a model of household demography. J. Artif. Soc. Soc. Simul. **16**(1), 8 (2013)

Hart, D.: Smart land-use analysis: the LUCIS model: land-use conflict identification strategy. J. Am. Plan. Assoc. **75**(1), 89–89 (2009). https://doi.org/10.1080/01944360802540166

Hatzopoulou, M., Hao, J.Y., Miller, E.J.: Simulating the impacts of household travel on greenhouse gas emissions, urban air quality, and population exposure. Transportation **38**(6), 871–887 (2011). https://doi.org/10.1007/s11116-011-9362-9

Horner, M.W., Widener, M.J.: The effects of transportation network failure on people's accessibility to hurricane disaster relief goods: a modeling approach and application to a Florida case study. Nat. Hazards **59**(3), 1619–1634 (2011). https://doi.org/10.1007/s11069-011-9855-z

Horni, A., Nagel, K., Axhausen, K.W.: The Multi-Agent Transport Simulation MATSim. Ubiquity Press London, London (2016)

Kaddoura, I., Kickhöfer, B., Neumann, A., Tirachini, A.: Agent-based optimisation of public transport supply and pricing: impacts of activity scheduling decisions and simulation randomness. Transportation **42**(6), 1039–1061 (2015). https://doi.org/10.1007/s11116-014-9533-6

Kaufman, S., Qing, C., Levenson, N., Hanson, M.: Transportation during and after hurricane sandy (2012). https://wagner.nyu.edu/impact/research/publications/transportation-during-and-after-hurricane-sandy. Accessed 23 Jan 2021

Keim, B.D., Muller, R.A., Stone, G.W.: Spatiotemporal patterns and return periods of tropical storm and hurricane strikes from Texas to Maine. J. Clim. **20**(14), 3498–3509 (2007)

Knutson, T.R., McBride, J.L., Chan, J., Emanuel, K., Holland, G., Landsea, C., Held, I., Kossin, J.P., Srivastava, A.K., Sugi, M.: Tropical cyclones and climate change. Nat. Geosci. **3**(3), 157–163 (2010). https://doi.org/10.1038/Ngeo779

Lawrence, M.B., Avila, L.A., Beven, J.L., Franklin, J.L., Pasch, R.J., Stewart, S.R.: Atlantic hurricane season of 2003. Mon. Weather Rev. **133**(6), 1744–1773 (2005)

Lu, Q.C., Peng, Z.R.: Vulnerability analysis of transportation network under scenarios of sea level rise. Transp. Res. Rec. **2263**, 174–181 (2011). https://doi.org/10.3141/2263-19

Lu, Q.-C., Peng, Z.-R., Zhang, J.: Identification and prioritization of critical transportation infrastructure: case study of coastal flooding. J. Transp. Eng. **141**(3), 04014082 (2015)

Lyons, G., Marsden, G.: Opening out and closing down: the treatment of uncertainty in transport planning's forecasting paradigm. Transportation (2019). https://doi.org/10.1007/s11116-019-10067-x

McCuen, R.H., Johnson, P.A., Robert M., R.: Hydraulic design series No. 2, Second Edition (No. FHWA-NHI-02–001). In: U.S. Department of Transportation (2002)

National Academies of Sciences, E., and Medicine: Transportation Resilience: Adaptation to Climate Change. The National Academies Press, Washington (2016)

National Research Council: Potential Impacts of Climate Change on US Transportation: Special Report 290, vol. 290. Transportation Research Board, Washington (2008)

Pachauri, R.K., Allen, M.R., Barros, V.R., Broome, J., Cramer, W., Christ, R., Church, J.A., Clarke, L., Dahe, Q., Dasgupta, P.: Climate change 2014: synthesis report. Contribution of Working Groups I, II and III to the fifth assessment report of the Intergovernmental Panel on Climate Change. Ipcc, (2014)

Parris, A.S., Bromirski, P., Burkett, V., Cayan, D.R., Culver, M.E., Hall, J., Horton, R.M., Knuuti, K., Moss, R.H., Obeysekera, J.: Global sea level rise scenarios for the United States National Climate Assessment (2012)

Picketts, I.M., Andrey, J., Matthews, L., Déry, S.J., Tighe, S.: Climate change adaptation strategies for transportation infrastructure in Prince George, Canada. Reg. Environ. Change **16**(4), 1109–1120 (2015). https://doi.org/10.1007/s10113-015-0828-8

Pregnolato, M., Ford, A., Robson, C., Glenis, V., Barr, S., Dawson, R.: Assessing urban strategies for reducing the impacts of extreme weather on infrastructure networks. R. Soc. Open Sci. (2016). https://doi.org/10.1098/rsos.160023

Pregnolato, M., Ford, A., Wilkinson, S.M., Dawson, R.J.: The impact of flooding on road transport: a depth-disruption function. Transp. Res. Part D Transp. Environ. **55**, 67–81 (2017)

Pritchard, D.R., Miller, E.J.: Advances in population synthesis: fitting many attributes per agent and fitting to household and person margins simultaneously. Transportation **39**(3), 685–704 (2012). https://doi.org/10.1007/s11116-011-9367-4

Saadi, I., Mustafa, A., Teller, J., Farooq, B., Cools, M.: Hidden Markov Model-based population synthesis. Transp. Res. B Methodol. **90**, 1–21 (2016). https://doi.org/10.1016/j.trb.2016.04.007

Saadi, I., Bruwier, M., Mustafa, A., Peltier, Y., Archambeau, P., Erpicum, S., Orban, P., Dassargues, A., Dewals, B., Pirotton, M.J.: Development trajectory of an integrated framework for the mitigation of future flood risk: results from the FloodLand project. Transp. Lett. **10**(5), 243–256 (2018a)

Saadi, I., Mustafa, A., Teller, J., Cools, M.: Investigating the impact of river floods on travel demand based on an agent-based modeling approach: The case of Liège, Belgium. Transp. Policy **67**, 102–110 (2018b). https://doi.org/10.1016/j.tranpol.2017.09.009

Shen, S., Feng, X., Peng, Z.R.: A framework to analyze vulnerability of critical infrastructure to climate change: the case of a coastal community in Florida. Nat Hazards (2016). https://doi.org/10.1007/s11069-016-2442-6

Siders, A.R.: Managed retreat in the United States. One Earth **1**(2), 216–225 (2019). https://doi.org/10.1016/j.oneear.2019.09.008

Taylor, M.A.P., Sekhar, S.V.C., D'Este, G.M.: Application of accessibility based methods for vulnerability analysis of strategic road networks. Netw. Spat. Econ. **6**(3–4), 267–291 (2006). https://doi.org/10.1007/s11067-006-9284-9

Testa, A.C., Furtado, M.N., Alipour, A.: Resilience of coastal transportation networks faced with extreme climatic events. Transp. Res. Rec. **2532**, 29–36 (2015). https://doi.org/10.3141/2532-04

Turek, D., de Valpine, P., Paciorek, C.J.: Efficient Markov chain Monte Carlo sampling for hierarchical hidden Markov models. Environ. Ecol. Stat. **23**(4), 549–564 (2016). https://doi.org/10.1007/s10651-016-0353-z

USACE: Sea-Level Change Curve Calculator (Version 2019.21). http://corpsmapu.usace.army.mil/rccinfo/slc/slcc_calc.html (2017).

Wdowinski, S., Bray, R., Kirtman, B.P., Wu, Z.: Increasing flooding hazard in coastal communities due to rising sea level: Case study of Miami Beach, Florida. Ocean Coast. Manag. **126**, 1–8 (2016)

Yin, W.H., Murray-Tuite, P., Ukkusuri, S.V., Gladwin, H.: An agent-based modeling system for travel demand simulation for hurricane evacuation. Transp. Res. Part C Emerg. Technol. **42**, 44–59 (2014). https://doi.org/10.1016/j.trc.2014.02.015

Zhuge, C., Shao, C., Wang, S., Hu, Y.: An agent- and GIS-based virtual city creator: a case study of Beijing, China. J. Transp. Land Use (2018). https://doi.org/10.5198/jtlu.2018.1270

Zhuge, C., Bithell, M., Shao, C., Li, X., Gao, J.: An improvement in MATSim computing time for large-scale travel behaviour microsimulation. Transportation (2019). https://doi.org/10.1007/s11116-019-10048-0

Ziemke, D., Nagel, K., Moeckel, R.: Towards an agent-based, integrated land-use transport modeling system. Proced. Comput. Sci. **83**, 958–963 (2016). https://doi.org/10.1016/j.procs.2016.04.192

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.