Using Climate Models to Estimate Urban Vulnerability to Flash Floods

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ABSTRACT

Climate change will impact urban infrastructure networks by changing precipitation patterns in a region. This study presents a novel vulnerability assessment framework for infrastructure networks against extreme rainfall-induced flash floods, with a specific application to transportation. The framework combines climate models, network science, geographical information systems (GIS), and stochastic modeling to compile a vulnerability surface (VS). Daily precipitation simulations for 2006–2100 from the Community Climate System Model, version 4 (CCSM4), are used to produce a stochastic simulation of extreme flash flood events in five U.S. cities—that is, Boston, Massachusetts; Houston, Texas; Miami, Florida; Oklahoma City, Oklahoma; and Philadelphia, Pennsylvania—under two different climate scenarios (RCP4.5 and RCP8.5). To assess the impact of these events, percentage drops in static (i.e., overall properties and robustness topological indicators) and dynamic (i.e., GIS accessibility and travel demand metrics) network properties are measured before and after simulated extreme events. The results of these metrics are inputs on a radar diagram to form a VS. Overall, the results show that changes in flash flood frequency due to climate change can have a significant impact on road networks, as was demonstrated recently in Houston, Texas. The magnitude of these impacts is chiefly associated with the geographic location of the cities and the size of the networks. The proposed framework can be reproduced in any city around the world, and researchers can use the results as guidelines for infrastructure design and planning purposes. Moreover, sensitivity analysis to varying greenhouse gas concentration trajectories can help local and national authorities to prioritize strategies for adaptation to climate change in more vulnerable regions.

1. Introduction

Our knowledge that the climate is changing is not new, but its impacts are just starting to be considered in many different fields, including for urban infrastructure design (Derrible 2017a,b). Studies have shown that climate change impacts, such as precipitation variations, along with other factors like temperature and sea level rise, will make
among the deadliest and most expensive weather-related disasters in the United States, especially in urban areas because of the concentration of population, inadequate stormwater systems, and impervious surfaces (i.e., roads and dry soils; Hong et al. 2013; Ashley and Ashley 2008).

One of the main urban infrastructure systems in cities that will be impacted by climate change is transportation, which plays a critical role for emergency response in the aftermath of hazards (Humphrey 2008). Services in transportation networks are highly dependent on weather-related hazards (Kermanshah et al. 2014), which can impose interruptions and delays in networks and lead to socioeconomic losses. Yet, in many cities, the design of urban drainage systems and stormwater management policies are based on historical data of extreme precipitation events (Ashley et al. 2005). Deviations from historical norms will widely affect many urban infrastructure systems, especially transportation systems, because of sewer overflows and flooding. Most current resilience/vulnerability studies use historical weather data as a baseline, with the assumption of stationary climate conditions. Recent studies, however, suggest that historical data do not adequately capture the impact of climate change (Milly et al. 2007; Mailhot and Duchesne 2010; Olsen 2015). With advances in climate modeling, thanks to a significant increase in computing power capacities, we now have access to high-resolution spatial and temporal scenarios of future climate conditions (Changnon and Kunkel 1999).

The literature on resilience to extreme events is abundant and is still growing. On the one hand, many studies use the capabilities of climate models to identify vulnerable areas, mostly to climate change. On the other hand, other studies analyze the resilience of transportation systems. Few studies, however, combine both and use climate models to analyze the resilience of urban infrastructure systems, which is the impetus for this study.

Leveraging novel computing capabilities and data accessibility (Ahmad and Derrible 2015; Cottrill and Derrible 2015; Kermanshah et al. 2016), we focus on the vulnerability of road systems to rainfall-induced flash floods under different future climate change scenarios. Overall, by combining the power of climate models, network science, geographical information systems (GIS), and stochastic modeling, the main goal of this article is to develop and apply a sound method to assess the vulnerability of road systems against climatically driven changes in the character (such as frequency and spatial pattern) of extreme rainfall-induced flash floods.

2. Background

Climate models currently tend to have horizontal grid sizes on the order of 100 km × 100 km resolution. While this resolution is generally sufficient for studying broad aspects of how the climate system will evolve over the next 100 years, the coarseness fails to provide the spatial resolution necessary to consider the occurrence of extreme rainfall flooding at a scale relevant for intricacy transportation networks. To address the need for higher-resolution projections of the climate, the coarse-resolution outputs can be downscaled using either statistical or dynamical techniques. In this study we exploit a public archive of downscaled simulations that used Multivariate Adaptive Constructed Analogs (MACA) downscaling (Abatzoglou and Brown 2012). This is a statistical downscaling approach that combines a priori information about weather patterns from historical data with information on how the mean state of the climate is shifting. The result is day-to-day gridded information about climate and weather on spatial scales relevant for city/county decision-making. While these data provide weather-scale information, it is important to note that they are not intended to provide weather forecasts but rather trends in the frequency of events.

To provide the flash flood scenarios for this study, we used the downscaled Community Climate System Model, version 4 (CCSM4), outputs of simulated daily precipitation data between 2006 and 2100 with spatial resolution of ~6 km (1/16°). This provided over 34000 possible days, which were screened for extreme flash flood events (methodology in section 3). The model outputs are freely available through an international collaboration referred to as phase 5 of the Coupled Model Intercomparison Project (CMIP5; Taylor et al. 2012). These data are considered the most comprehensive library of state-of-the-art climate model outputs and are used to develop the Intergovernmental Panel on Climate Change (IPCC) Assessment Reports, which are the most broadly accessed reference for policy makers on climate change (IPCC 2013). The framework presented in this study can be reproduced with all of the climate model outputs available in the CMIP5 database. To see the impacts of climate change on extreme precipitation, we utilized outputs assuming two different greenhouse gas concentration trajectories, that is, representative concentration pathways (RCPs) that capture the level of human actions to curb climate change; RCP4.5 represents moderate climate action, and RCP8.5 represents no climate action and high emissions (Moss et al. 2010).

Relevant to our study, few studies attempt to set the extreme thresholds of climate parameters in a region, but they base their estimates on past events as opposed to climate projections; for example, the number of extreme wet days was defined as the number of days per year when the daily rainfall rate exceeds a threshold of
the 95th percentile of wet days (Frich et al. 2002; Zhang and Yang 2004). One major study on extreme events in Europe classified the extreme events based on the rarity, intensity, and severity of events (Beniston et al. 2007). From this definition, Beniston et al. (2007) came up with three ways to identify extreme events (specifically extreme rainfall): 1) maxima (e.g., annual maximum dry- and wet-spell lengths), 2) percentiles (e.g., 95th percentile of summer 1-day totals), and 3) threshold-based indices (e.g., means of maximum summer 1-day and winter 5-day totals). One study defined extreme rainfall-inducing flash floods as 2.54 cm h^{-1} rainfalls (Brooks and Stensrud 2000) and another adjusted the scale to integrate rainfall over 24 h (Smith et al. 1994). Overall, forecasting the occurrence of flash floods is often seen as one of the most challenging tasks in hazard forecasting for meteorological researchers (Doswell et al. 1996).

In addition, resilience to extreme flooding is more than a function of physical exposure. Two cities may face identical physical exposure to a climate-related hazard but show widely differing characteristics of vulnerability because of their network’s topological and physical characteristics, therefore potentially impacting their resiliency and coping capacity substantially (IPCC 2007). In particular, within the pool of studies listed above, transportation is often omitted. While there are some climate impact studies on transportation infrastructure, they tend to be based on empirical assessments on traffic flow disruptions due to adverse climate (e.g., precipitation, snow, and wind; Koetse and Rietveld 2009), and they cannot therefore be transferred to other areas. Few studies analyze the impacts of climate change on urban transportation networks; two exceptions are Chang et al. (2010) who studied flood-induced travel disruptions due to climate change in Portland, Oregon, and Pregnolato et al. (2016) who proposed an impact assessment framework of flood-induced disruptions in road networks and quantified different adaptation options in Newcastle upon Tyne, United Kingdom. Many other studies on road transportation systems analyze the impact of adverse weather on crashes, congestion, and travel time. Because of the complexity of the relationship between these concepts, most of the research in this area has been concentrated on the partial relationships between weather and crashes and weather and congestion (Stern and Zehavi 1990; Maycock 1995). On weather and crashes, studies showed that fog and wind will increase the number of crashes (Edwards 1996; Hermans et al. 2006), but the most important climate variable is precipitation. On weather and congestion, numerous studies show that there is a significant decrease in traffic speed due to adverse weather conditions, especially precipitation (Martin et al. 2000; Maze et al. 2006).

According to these studies, we cannot generalize the effect of precipitation on traffic speed with other climate parameters like temperature and wind speed, which appears to have small and negligible effects (Koetse and Rietveld 2009). This is one of the main reasons that we have chosen to concentrate on road segment failure probability due to extreme precipitation events and offer both analytics at the road segment scale and at the city scale.

3. Methodology

Road systems are complex networks composed of roads and intersections (Peiravian et al. 2014). In this study, the unit of analysis is the road segment, which is defined as a part of a road that links two consecutive intersections. The premise is that if a road fails, for example, if it is affected by a flash flood, traffic can be diverted using the intersections on each side of a segment. From a network science point of view, we are adopting a primal graph approach (Porta et al. 2006) that sees intersections as nodes and road segments as links. The road system is therefore assimilated to a graph $G$ with $N$ nodes (i.e., intersections) and $L$ links (i.e., segments) such that $G = \{N, L\}$. This process was done for each case study using a GIS tool that converts GIS shapefiles into networks (Karduni et al. 2016).

In this study, we applied the methodology to five U.S. cities: Boston, Massachusetts; Houston, Texas; Miami, Florida; Oklahoma City, Oklahoma; and Philadelphia, Pennsylvania. We selected these cities because they are major cities that commonly experience flash floods, thus making their road networks vulnerable to disruption. The raw transportation data for these cities were collected from the U.S. Census Bureau’s Topologically Integrated Geographic Encoding and Referencing (TIGER) database (U.S. Census Bureau 2013). We made no edits to the road networks, thus assuming they are unchanged in the future. The main rationale is for the model to highlight the current urban areas that are vulnerable so that effort and resources can be put into making them more robust in the future.

As illustrated in Fig. 1, the framework of this paper consists of 1) selecting urban transportation systems data, that is, road shapefiles, and assimilating them to networks (i.e., a primal graph approach; Porta et al. 2006); 2) extracting historical extreme precipitation thresholds to define climate failure rates using the CMIP5 MACA downscaled climate model of CCSM4 from the U.S. National Center for Atmospheric Research for two RCPs (i.e., RCP4.5 and RCP8.5) of daily precipitation data from 2006 to 2100 (Taylor et al. 2012; Abatzoglou and Brown 2012; Livneh et al. 2013);
3) adopting a stochastic modeling approach to simulate extreme rainfall-induced flash flooding; 4) validating the modeling approach with real data from past extreme flash floods that caused urban road disruptions; 5) combining the resilience metrics into a vulnerability surface (VS) that captures resilience of road systems (Kermanshah and Derrible 2016); and 6) comparing the VSs of different urban road systems. In the following sections, we describe each of these steps.

a. Extreme flash flood simulation

We assign a failure probability to every single street segment in our system (i.e., to every \( l_i \) in \( L \)). Because of the level of uncertainty that is present, stochastic modeling is preferable for extreme flash flood simulation. The goal is therefore to use the deterministic output from climate models and feed them into a stochastic model. Stochastic modeling offers a computationally inexpensive and modular approach to assess the probability of road failure at the scale of an individual road segment. Specifically, we implement the stochastic failure behavior model developed in Kröger and Zio (2011), which was initially developed for power grid failures and later applied to transportation (Wisetjindawat et al. 2015, 2017).

The probability \( p_i \) that link \( i \) fails under an extreme flash flood formulation is defined as

\[
p_i = 1 - e^{-\lambda_i \eta_i},
\]

where \( \lambda_i \) is the climate failure probability for link \( i \), and \( \eta_i \) is the length parameter for link \( i \). All of the variables used in the methodology are defined in Table 1.

The model accounts for a climate failure probability \( \lambda_k \) assigned to an individual climate grid \( k \), such that \( 0 < \lambda_k < 1 \). This failure probability \( \lambda_k \) accounts for the likelihood of a certain extreme precipitation event in that climate grid. As mentioned earlier in (section 2), there is no consensus on the definition of extreme precipitation events. Therefore, depending on different approaches and available datasets, each study has its own definition for these extreme events. Here, to set that threshold for extreme precipitation events, we use the fundamental properties of extreme events: they are rare (i.e., low frequency of happening) and intense (i.e., significant deviations from average events) events that can cause severe losses (Beniston et al. 2007). Therefore, we look into all daily precipitation data for the entire historical database (i.e., 1950–2005) for every grid cell within the road network to identify the grid with the minimum value of the 95th percentile of daily precipitation values. In the other words, we select the minimum daily precipitation value of 5% threshold for all the grid cells in each network to capture the right tail of the distribution as an historical extreme precipitation event. Climate failure probabilities are then determined when precipitation values exceed the minimum 5% threshold in the study area. This approach makes

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<th>TABLE 1. Stochastic model parameters.</th>
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<td>Parameter</td>
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extreme precipitation event simulation specific to any region and enables its reproducibility for different cities under different climate scenarios. Consequently, the climate failure probability of the entire grid cell \( \lambda_k \) is the proportion of the frequency of extreme precipitation events (defined as the minimum 5% threshold in the entire grid cells of the study area for historical data) to the entire number of days in the climate simulation (i.e., 2006–2100). As a small note, we decided to use the entire forecasting database, which included several years before the publication of this article (i.e., 2006–17). This decision was made to be consistent with the database available, but it should not have any significant impact on the results. Any future study can opt to include or omit any past years from the database on climate forecasts. We then define the failure rate \( \lambda_l \) of each link to be equal to its respective \( \lambda_k \), matching the location of the link with the location of climate grids (interpolating for roads that belong to two or more grids).

In this stochastic modeling approach, the impact of link length \( l_i \) (i.e., the longer the road segment, the more likely it is to fail) on link \( i \) is also taken into account as a length parameter. To make this parameter dimensionless for the stochastic model, we divide each link’s length by the average length of links that were impacted during previous flash flood events in the United States, that is, \( l_{\text{AvgCritical}} \). To find this critical length, we use the National Severe Storms Laboratory’s Severe Hazards Analysis and Verification Experiment (SHAVE) data, which is a public near-real-time expert-based survey database that includes the characteristics of the storm-targeted flash flood events and their impacts (Gourley et al. 2013). In addition to the basic classification of the events (e.g., flood frequency, flood type, water movement, water depth, and land use), one of the main advantages of this database is that it contains 10 different categories of impacts for flash floods from “no impact” to “rescues/fatalities/injuries.” With these categories we can determine the extreme flash flood events that impacted road networks (i.e., impact classes: “street/road flooding,” “road closure,” “inundation,” “evacuation,” “stranded cars,” and “rescues/fatalities/ injuries”; Calianno et al. 2013). Therefore, after a comprehensive analysis of the entire SHAVE database for all of the events that impacted U.S. road networks, the average critical length was found to be 596 m. Other information from the SHAVE database was also used to partially validate the stochastic modeling approach for extreme flash flood simulation (see section 4a).

Therefore, the length parameter \( \eta_i \) that we use in the stochastic equation of link \( i \) is defined by

\[
\eta_i = \frac{l_i}{l_{\text{AvgCritical}}},
\]

where \( l_i \) is the length of link \( i \), and \( l_{\text{AvgCritical}} \) is the average critical length of the impacted links during the previous real flash flood events.

Finally, to simulate extreme flash floods for each climate scenario, we generate a random number in the range [0, 1] from a uniform distribution for every link, and if the generated number is lower than the failure probability, we remove it from the road system. The scenario analysis exercise consists in repeating this procedure multiple times for one network. After several tests, we found that repeating the procedure more than 20 times did not change the results significantly, and we therefore ran the procedure 20 times for each city. In addition, repeating the procedure more than 20 times can become unreasonable since the computation of betweenness centrality (section 3c(2)) can be particularly slow. Once all runs are completed, the results are averaged and compiled into a VS (section 3b). Finally, we note that we are not using any hydrologic modeling to simulate the impact of stormwater runoffs. Spatial correlation between the road segments is, however, taken into account since neighboring road segments tend to have similar climate failure rates \( \lambda_i \).

b. Vulnerability surface method

The VS method offers a pragmatic approach for combining different resiliency/robustness/vulnerability indicators into one single parameter to determine the vulnerability of road systems to flash floods. This method was previously applied to transportation systems in California to assess their vulnerability against earthquakes (Kermanshah and Derrible 2016). The vulnerability of transportation systems against extreme events depends on many factors that only can be captured through comprehensive analyses before and after an extreme event. Several studies tried to categorize different metrics to quantify the impacts of extreme events on transportation systems (Snelder 2010; Faturechi and Miller-Hooks 2015). Snelder (2010) classified robustness indicators into three categories: 1) static indicators, which are independent of the traffic flow and are related directly to the network’s property; 2) dynamic indicators, which are associated with traffic flows; and 3) indirect indicators, which are associated with travel time.

To capture different aspects of resiliency in road networks, we use infrastructure characteristics [i.e., overall properties percentage change in road length; section 3c(1)] and network robustness topological indicators [i.e., maximum edge betweenness centrality
For each climate scenario, VDs are calculated (i.e., VD1, VD2, and VD3 in Fig. 2). For each climate scenario, the final VS consists of the average of each VD. The final result of this process is two different VSs (i.e., two vulnerability dimensions) for each of the climate scenarios, the failure probability of which is measured as the average total affected length of roads. Changes in these static indicators can show the level of exposure to flash floods, which is directly connected with the vulnerability of road networks. By removing more links from the road networks we are reducing the capacity of the system and we are also eliminating alternative route options in the system that can handle severe traffic congestion in the aftermath of extreme events. Here, to keep the method relatively simple and to avoid over-representing network characteristics, we only select the total length affected \( \Delta L \).

2) Robustness topological indicators: betweenness centrality

Centrality is a measure of importance of an element in a network. Three typical indicators are calculated: degree, closeness, and betweenness centrality (Derrible 2012; Porta et al. 2009; Wang et al. 2011). Out of these three, betweenness centrality deserves attention because it measures how much a node/link is used to connect any pair of nodes. More formally, let \( n_{jk} \) be the total number of shortest paths linking nodes \( j \) and \( k \), and \( n_{jk}(i) \) be the number of these paths going through node \( i \). Then the probability of using node \( i \) is simply \( n_{jk}(i)/n_{jk} \). Doing this for all paths, the betweenness centrality is

\[
C_B(n_i) = \sum_{jk} \frac{n_{jk}(i)}{n_{jk}}.
\]

A similar procedure is used to determine edge betweenness, which is more relevant in our case because we are working with road networks. A link in the network (i.e., a road segment) with high betweenness centrality is more central, and in our case, this can be compared with larger traffic volumes. When impacted, these road segments disrupt the traffic more heavily, thus making the network more vulnerable (Duan and Lu 2013).

Here we only focus on road segments to avoid over-representation from one group of metrics in the VS method. In this study, the notation for maximum edge betweenness centrality is \( C_{Be}^{\text{max}} \). From Eq. (3), we can see that the betweenness centrality is a size-sensitive metric, which means a larger network has larger maximum edge betweenness centrality. To normalize the comparison between different road networks, we use percentage difference between maximum betweenness centralities before and after an extreme flash flood as a vulnerability dimension.
3) GIS ACCESSIBILITY METRIC (SERVICE AREA)

Access coverage to emergency stations (e.g., fire stations and hospitals) is crucial after extreme events. Access to these locations is typically observed as spatiotemporal terms. The definition of a network service area in transportation science relates to an area that includes every accessible location in the network within a specific spatiotemporal constraint. The rationale here is to measure the drop in a service area before and after an extreme event. These results can be useful for local authorities in locating emergency stations (e.g., hospitals, shelters, fire stations, and police stations).

To evaluate the performance of a road network after extreme flash floods events, we examine the percentage changes in spatial accessibility after these events. Specifically, we randomly select 100 points within each road network to measure their spatial accessibility level in two major categories: walking distance, that is, 1-km short-distance accessibility, and commuting distance, that is, 5-km long-distance accessibility. More specifically, we measure the area made by the polygon that extends 1 and 5 km away from a specific point, following link lengths. As a result, for the five road networks, the two climate scenarios, and the 20 simulations, we examine the percentage change in two different service areas of 1 and 5 km around 100 randomly located points. The reason behind randomly locating the point is the unpredictable nature of flash floods, as well as the convenient reproducibility of the approach (i.e., fewer data requirements). Note that, although this is unlikely to be a significant source of problems, we added a condition that the randomly selected points needed to be at least 200 m away from one another to ensure that not all points end up in the same area. Therefore, the service area change is measured as

$$
\Delta A_i = \frac{\sum A_{i}^{\text{pre}} - \sum A_{i}^{\text{post}}}{\sum A_{i}^{\text{pre}}},
$$

where $\sum A_{i}^{\text{pre}}$ is the total service area from the randomly selected location $i$ in pre–flash flood conditions and $\sum A_{i}^{\text{post}}$ is the total service area from the randomly selected location $i$ in post–flash flood conditions. For the input of the VS method, as a vulnerability dimension, we use the average of $\Delta A_i$ for the 20 runs of each climate scenario.

4) TRAFFIC FLOW CHANGES

Several datasets exist that contain information on home-to-work trips, including the Census Transportation...
Planning Products (CTPP) and the Longitudinal Employer Household Dynamics (LEHD) datasets (Kermanshah and Derrible 2017). However, travel patterns during extreme events cannot be compared with typical daily patterns, and it is questionable whether using these datasets offers higher accuracy than random traffic patterns. Instead, to simulate traffic flow changes, we chose to select 1000 randomly located points in a city and compare how shortest-path distances between one another are affected between normal conditions and during extreme flash flooding. Put differently, by selecting 1000 points and by linking them, we are essentially simulating random traffic patterns. Moreover, although there is no theoretical basis for selecting 1000 points, we note that Giacomini and Levinson (2015) found that using and linking at least 500 randomly selected points adequately captured real traffic patterns.

The next step is to define the constraints that disturb the connection between the nodes, which, in our case are the extreme flash floods. Here we examine how the 499 500 trips are affected by the extreme flooding events. The trips after the extreme events (i.e., post–flash flood trips $T_{\text{post}}$) can be divided into four categories (Kermanshah and Derrible 2016):

$$T_{\text{post}} = T_{A}^{\text{post}} + T_{B}^{\text{post}} + T_{C}^{\text{post}} + T_{D}^{\text{post}},$$

where $T_{A}^{\text{post}}$ and $T_{B}^{\text{post}}$ are the completed trips after the extreme flash flood that used the exact same route and a longer route, respectively; and $T_{C}^{\text{post}}$ and $T_{D}^{\text{post}}$ are the uncompleted trips after the extreme flash floods because a node is isolated from its destination or a node is located directly within an impacted area, respectively. From Eq. (5), we can define five metrics [Eqs. (6)–(10)] that can capture the impacts of extreme flash floods on the road network. The first metric $\tau_A$ is the proportion of the intact trips, the second metric $\tau_B$ is the proportion of all trips that were forced to travel longer distances, the third metric $\tau_C$ is the percentage of the trips that could not be completed because they were isolated, the fourth metric $\tau_D$ is the percentage of the affected trips that were directly located within an impacted area, and the fifth metric $\tau_{AB}$ is the proportion of completed trips that specifically had to travel longer distances. Among these five metrics, we use $\tau_C$ and $\tau_D$ as two standardized (i.e., numbers between 0 and 1) vulnerability dimensions; that is, the higher their value (i.e., higher rate of uncompleted trips), the more vulnerable the system:

$$\tau_A = \frac{T_{A}^{\text{post}}}{T_{\text{pre}}},$$

(6)

$$\tau_B = \frac{T_{B}^{\text{post}}}{T_{\text{pre}}},$$

(7)

$$\tau_C = \frac{T_{C}^{\text{post}}}{T_{\text{pre}}},$$

(8)

$$\tau_D = \frac{T_{D}^{\text{post}}}{T_{\text{pre}}},$$

(9)

$$\tau_{AB} = \frac{T_{A}^{\text{post}}}{T_{A}^{\text{pre}}} + \frac{T_{B}^{\text{post}}}{T_{B}^{\text{pre}}},$$

(10)

4. Results and discussion

The minimum 5% thresholds for historical daily precipitation (cm day$^{-1}$) for Boston, Houston, Miami, Oklahoma City, and Philadelphia are 20.08, 23.15, 24.07, 20.87, and 19.75, respectively. Here, from the point map obtained from daily precipitation climate data, we use a kriging method to generate a raster map on top of the road networks to determine climate failure rates for each road segment (Fig. 3 shows the results for the RCP8.5 climate scenario). We note that according to the U.S. National Weather Service Storm Data Directive, “a depth of approximately six inches [15.24 cm] of fast-moving water should be considered as it will knock a person off his/her feet and begin to cause some cars to move out of control” (https://www.ncdc.noaa.gov/stormevents/pd01016005curr.pdf). Values calculated for the five cities are higher, but we need to take into account that some of this precipitation is intercepted before reaching the ground, some directly infiltrates the ground, and some reaches the sewer before the flow turns into a flash flood.

a. Validating the stochastic modeling approach

To partially validate the stochastic modeling approach for extreme flash flood events, we again use the SHAVE dataset. Essentially, we compare whether historically impacted areas match with forecasted impacted areas. For example, with 55 extreme flash flood events, Oklahoma City had the highest frequency of extreme flash flood events that caused disruptions in the road network among the five cities studied. Specifically, more than 67% of these events (i.e., 37 extreme flash flood events) happened in the region where we calculated climate failure rates above 50%, that is, $\lambda_{i} \geq 0.068$ (note that $\lambda_{i}$ is independent of the SHAVE dataset). The results are shown in Fig. 4 for the RCP4.5 climate scenario. Although this is only a partial validation process these results suggest that there is a significant correlation between heavy rainfalls and extreme flash floods.
b. Static indicators response to simulated extreme flash floods

Basically, the small numbers of removed roads after extreme flash floods might imply that these events have no substantial impacts on road network. However, for complex nonlinear systems such as road systems, relatively small changes can have substantial impacts on the final outcome (Taleb 2012). The first important point about the drops in road length of the road networks is that in both climate scenarios we have nearly the same number of road lengths that are removed (Table 2). However, the locations of removed links are different, which causes different changes in betweenness centralities. From Table 2, the road systems of Boston, Miami, and Philadelphia only lost 1.5%–5% of their road lengths after flash floods. In contrast, the percentage of removed road lengths for Houston and Oklahoma City are almost 3 times higher. Nonetheless, we can see that although Miami’s road system appears not to be severely affected in terms of road length, it has a significant drop in edge betweenness with a drop in $C_{Be}^{\text{max}}$ of 19.87% in the RCP8.5 climate scenario.

All of the road networks experience higher drops in $C_{Be}^{\text{max}}$ for the RCP8.5 climate scenario. The drops in Houston are higher by a factor of more than 7 for the RCP8.5 climate scenario relative to the RCP4.5 climate scenario. These results alone substantiate the need for multiple vulnerability indicators; hence our VS approach.

c. Dynamic indicators response to simulated extreme flash floods

Changes in traffic flow patterns are different for the five cities, suggesting different levels of vulnerability in each case study (Table 3). In Boston and Philadelphia, more than 93% of the trips were completed, that is, $\tau_A + \tau_B$, after the extreme flash floods for both climate scenarios. Miami was more affected with a percentage of completed trips of more than 70% for both climate scenarios (i.e., $\tau_A + \tau_B = 70.35\%$ for RCP4.5 and $\tau_A + \tau_B = 74.93\%$ for RCP8.5). In contrast, the road systems of Houston and Oklahoma City were impacted significantly after the extreme flash floods. Less than 7% of the trips were not affected (i.e., $\tau_C + \tau_D$) in Houston in both climate scenarios.

The impact of climate change on traffic cannot be trivially determined from purely comparing traffic flow changes between the two climate scenarios. In four of the five road networks—Boston, Houston, Oklahoma City, and Philadelphia—the number of uncompleted trips, that is, $\tau_C + \tau_D$, was higher for RCP8.5. Among these four cities the difference between the percentage of uncompleted trips for the two climate scenarios was not significant for Oklahoma.
City (i.e., $\tau_C + \tau_D = 44.42\%$ for RCP4.5 and $\tau_C + \tau_D = 44.95\%$ for RCP8.5) and Philadelphia (i.e., $\tau_C + \tau_D = 6.10\%$ for RCP4.5 and $\tau_C + \tau_D = 6.49\%$ for RCP8.5). On the contrary, Miami has a higher drop in the number of uncompleted trips in the RCP4.5 climate scenario, that is, $\tau_C + \tau_D = 29.64\%$.

The results for service area changes for short- and long-distance accessibilities in the five case studies are shown in Table 4. In all of the networks and for both of the climate scenarios, long-distance accessibility drops are higher than short-distance accessibility drops. We can see a significant difference in cities like Houston whose long-distance accessibility drop is 3 times higher than its short-distance accessibility drop for the RCP4.5 climate scenario. This result could suggest that affected people after extreme flash floods may have problems reaching...
emergency stations (e.g., hospitals) with their vehicles; concurrently, emergency management agencies would have problems reaching the people stranded in the flooded roadways. These drops in service areas for Houston reach 30% for long-distance accessibilities.

In all of the networks, except Oklahoma City, the service area drops are higher for the RCP8.5 climate scenario (in Oklahoma City, long-distance accessibility drops are similar in both climate scenarios). Moreover, different levels of drops in service areas in different road networks (e.g., Houston service area changes versus Miami service area changes) indicate that the geographical location of a road network plays a crucial role in the resilience of these networks against extreme events.

d. Vulnerability surface results

We have defined 6 different VDs to compile the VS. Figure 5 presents the final VS results for each city for the two climate scenarios (we set the maximum for each axis to 0.5). For the RCP4.5 climate scenario, Houston and Oklahoma City have the highest VSs among other road networks with 0.0625 and 0.0783, respectively (Table 5). For the same climate scenario, Philadelphia has the lowest VS with 0.0034. These results suggest that Philadelphia’s road network is less vulnerable to extreme flash floods than all other cities studied. For all cities, the VS results for RCP8.5 follow overall similar patterns to the results for RCP4.5. For RCP8.5, Houston and Oklahoma City have the highest VSs again; Houston’s VS is notably more than 16% higher than the VS of Oklahoma City. The VS of Miami in the RCP4.5 climate scenario is in the middle of the five road networks. The Philadelphia VS for RCP8.5 is the lowest of all road networks (i.e., VS = 0.0106).

Comparing the VS results of each city, we find that the VS of all cities are larger—thus more impacted—for RCP8.5. There are significant differences between the VSs of RCP4.5 and RCP8.5 for the road systems of Boston, Houston, Miami, and Philadelphia with an 80%, 42%, 40%, and 103% increase, respectively. In Oklahoma City the VSs for the two climate scenarios are almost the same with only a 4% difference. We should add that despite Philadelphia’s low VSs in both climate scenarios, the impacts of climate change on the vulnerability of the road system of the city is more significant than the other cities.

5. Conclusions

This study explores the impacts of climate change on the vulnerability of road systems to rainfall-induced extreme flash floods in two climate scenarios.

<table>
<thead>
<tr>
<th>Road network</th>
<th>t_{A} (%)</th>
<th>t_{B} (%)</th>
<th>t_{C} (%)</th>
<th>t_{D} (%)</th>
<th>t_{AB} (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Boston</td>
<td>65.27</td>
<td>29.95</td>
<td>1.78</td>
<td>3.00</td>
<td>31.45</td>
</tr>
<tr>
<td>RCP8.5</td>
<td>35.44</td>
<td>59.19</td>
<td>0.98</td>
<td>4.39</td>
<td>62.55</td>
</tr>
<tr>
<td>Houston</td>
<td>6.79</td>
<td>56.23</td>
<td>27.51</td>
<td>9.46</td>
<td>89.22</td>
</tr>
<tr>
<td>RCP8.5</td>
<td>5.86</td>
<td>55.53</td>
<td>31.86</td>
<td>6.75</td>
<td>90.46</td>
</tr>
<tr>
<td>Miami</td>
<td>45.24</td>
<td>25.11</td>
<td>26.80</td>
<td>2.84</td>
<td>35.70</td>
</tr>
<tr>
<td>RCP8.5</td>
<td>50.88</td>
<td>24.05</td>
<td>22.84</td>
<td>2.23</td>
<td>32.10</td>
</tr>
<tr>
<td>Oklahoma City</td>
<td>13.16</td>
<td>42.43</td>
<td>30.84</td>
<td>13.58</td>
<td>76.33</td>
</tr>
<tr>
<td>RCP8.5</td>
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<tr>
<td>Philadelphia</td>
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<td>40.10</td>
<td>1.36</td>
<td>4.74</td>
<td>42.70</td>
</tr>
<tr>
<td>RCP8.5</td>
<td>43.76</td>
<td>49.75</td>
<td>2.14</td>
<td>4.35</td>
<td>53.20</td>
</tr>
</tbody>
</table>

Table 4. Service area changes for short- and long-distance accessibilities after extreme flash floods in two climate scenarios.
flash floods. Here, we developed a stochastic modeling approach to assess the vulnerability of every single road segment in a transport system using outputs from downscaled state-of-the-art climate models and road maps. Once a failure probability is assigned to every link, we analyze two climate scenarios (i.e., RCP4.5 and RCP8.5) and collect static (i.e., infrastructure characteristics and network robustness topological indicators) and dynamic (i.e., changes in accessibility and travel demand characteristics) metrics. After these processes, we combine the measures for each climate scenario onto a vulnerability surface (VS). The novelty of this research stems from the use of local climate conditions that have proven effective to assess the vulnerability of entire areas, as well as the level of service to assess the impact of extreme flash floods using the VS method.

This study offers a number of novel approaches, which can be adopted in future analyses on the impact of climate change on transportation networks. First, using state-of-the-art climate models offers a process-driven perspective on the frequency of extreme events that not only relies on historical data but that also uses projected data to simulate extreme events. Second, stochastic models offer a computationally inexpensive and modular approach to assess the vulnerability of road systems.

Third, in the absence of travel data, sampling random nodes and calculating the edge betweenness centralities of individual links can be used as a proxy to level of service. This general framework can be applied to any spatial system beyond transportation systems such as water, gas, and electricity systems.

One of the advantages of this method is its reproductibility and applicability. Because this research is based on readily available and free data (i.e., climate model outputs from the Coupled Model Intercomparison Project), and thanks to the simple nature of the methodology, any local planning agency from a town in Oklahoma to a town in Bangladesh can assess critical elements of their road system.

From a planning point of view, the results of this study can be used for both local and national government authorities. Local government can alter their urban infrastructure design criteria to adapt to climate change. These changes in design criteria, especially in stormwater management systems, can make the city’s infrastructure more robust. They can also implement many green infrastructures and low impact development (LID) technologies in the city—such as rain gardens and bioswales—to diminish the destructive impacts of extreme flash floods. Moreover, this type of research can

![Fig. 5. VSs for five road networks for the two different climate scenarios.](image)

**Table 5. Vulnerability assessment results using the VS method.**

<table>
<thead>
<tr>
<th></th>
<th>VD1</th>
<th>VD2</th>
<th>VD3</th>
<th>VD4</th>
<th>VD5</th>
<th>VD6</th>
<th>VS</th>
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<tr>
<td></td>
<td>ΔL</td>
<td>ΔΔL</td>
<td>ΔΔΔL</td>
<td>ΔΔΔΔL</td>
<td>ΔΔΔΔΔL</td>
<td>ΔΔΔΔΔΔL</td>
<td></td>
</tr>
<tr>
<td>Boston</td>
<td>RCP4.5</td>
<td>0.0376</td>
<td>0.0869</td>
<td>0.0566</td>
<td>0.0978</td>
<td>0.0178</td>
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<tr>
<td></td>
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<td>0.0619</td>
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<td>0.0098</td>
<td>0.0439</td>
</tr>
<tr>
<td>Houston</td>
<td>RCP4.5</td>
<td>0.0871</td>
<td>0.0381</td>
<td>0.0861</td>
<td>0.2893</td>
<td>0.0275</td>
<td>0.0946</td>
</tr>
<tr>
<td></td>
<td>RCP8.5</td>
<td>0.0857</td>
<td>0.2954</td>
<td>0.1191</td>
<td>0.3071</td>
<td>0.3186</td>
<td>0.0675</td>
</tr>
<tr>
<td>Miami</td>
<td>RCP4.5</td>
<td>0.0273</td>
<td>0.1045</td>
<td>0.0213</td>
<td>0.0295</td>
<td>0.268</td>
<td>0.0284</td>
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<tr>
<td></td>
<td>RCP8.5</td>
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<td>0.1987</td>
<td>0.0408</td>
<td>0.0606</td>
<td>0.2284</td>
<td>0.0223</td>
</tr>
<tr>
<td>Oklahoma City</td>
<td>RCP4.5</td>
<td>0.1079</td>
<td>0.1451</td>
<td>0.0846</td>
<td>0.2457</td>
<td>0.3084</td>
<td>0.1358</td>
</tr>
<tr>
<td></td>
<td>RCP8.5</td>
<td>0.113</td>
<td>0.1899</td>
<td>0.0783</td>
<td>0.2452</td>
<td>0.3344</td>
<td>0.1151</td>
</tr>
<tr>
<td>Philadelphia</td>
<td>RCP4.5</td>
<td>0.0304</td>
<td>0.0463</td>
<td>0.0263</td>
<td>0.0795</td>
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<td>0.0474</td>
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<tr>
<td></td>
<td>RCP8.5</td>
<td>0.0348</td>
<td>0.157</td>
<td>0.0518</td>
<td>0.1165</td>
<td>0.0214</td>
<td>0.0435</td>
</tr>
</tbody>
</table>
inform local governments on how to provide appropriate information to people to change their travel behavior during large precipitation events (Shabanpour et al. 2017). National government authorities, especially in countries with centralized systems, can prioritize adaptation policies (e.g., infrastructure maintenance) in regions with a higher risk of vulnerability and assign more resources to them. Focusing on the planning and design of transportation networks in a vulnerable region can reduce possible economic losses in the future. Moreover, transportation planners can use the VS method for different series of analyses and use the results for future design aspects of the transportation networks.

Overall, the outcomes of the vulnerability assessment for road networks may be completely different in every city because of geographic location, the size of the network, and also the projection of climate scenarios. Nonetheless, climate change is bound to seriously impact cities across the United States and the world, and novel modeling techniques are necessary if we are to successfully adapt the urban infrastructure systems that are critical to city life.

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REFERENCES


