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Testing the Hurricane Evacuation Modeling Package (HEMP)

2. Author(s)
Ruijie “Rebecca” Bian, Ph.D., P.E.

3. Performing Organization Name and Address
Louisiana Transportation Research Center
4101 Gourrier Ave
Baton Rouge, LA 70808

4. Sponsoring Agency Name and Address
Louisiana Department of Transportation and Development
P.O. Box 94245
Baton Rouge, LA 70804-9245

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13. Abstract
This project studied if and how behavioral models and traffic simulation frameworks created beforehand could be used to predict hurricane evacuation patterns in a new storm setting, with the anticipation of being able to conduct a real-time simulation in the future. Using publicly available data, this study first created synthetic populations by year for the study region of New Orleans, Louisiana. Findings from this process show that simulations of evacuation behavior can only be performed for storms that occurred between 2013 and two years prior to the current year. Additionally, it may not be appropriate to use population data from a different year to simulate evacuation behavior in a current year due to population migration.

Using synthetic populations created for 2021, this project utilized behavioral models estimated beforehand to simulate evacuation choices for households during Hurricane Ida, which facilitated discussions about model transferability. It was found that the lognormal distance function parameters

in the evacuate/stay and departure timing joint choice models, as well as the destination risk perception values in the destination choice model, are the two most critical factors that need to be updated. Both factor updates are related to storm characteristics and can be completed with live storm feeds, which indicates that real-time data input is indispensable in improving prediction accuracy.

In simulating evacuation traffic, this project tested 20 simulation scenarios to look for a traffic assignment model with drivers' route choice parameters embedded that could provide the best fit for traffic observed during the Hurricane Ida evacuation. It was found that the stochastic shortest path model, which minimizes travel time and assumes 50% of informed drivers, performed the best.

Overall, this study highlights the necessity and challenges of having real-time data (e.g., population profiles, storm forecasts, and near-real-time background traffic) in hurricane evacuation simulations. This information enhances the usefulness of estimated statistical models in practical applications and emphasizes the importance of considering human components, including demographic profiles and choice behavior, in creating digital twins to better support future disaster management.

Project Review Committee

Each research project will have an advisory committee appointed by the LTRC Director. The Project Review Committee is responsible for assisting the LTRC Administrator or Manager in the development of acceptable research problem statements, requests for proposals, review of research proposals, oversight of approved research projects, and implementation of findings.

LTRC appreciates the dedication of the following Project Review Committee Members in guiding this research study to fruition.

LTRC Administrator/Manager
Elisabeta Mitran, Ph.D.
Safety Research Manager

Members
Faith A. Roussell
Melton Gaspard
John Broemmelsiek
Lucy Kimbeng
Collin Arnold
Lt. Joshua Nations

Directorate Implementation Sponsor
Chad Winchester, P.E.
DOTD Chief Engineer

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By
Ruijie "Rebecca" Bian, Ph.D., P.E.

Louisiana Transportation Research Center
4101 Gourrier Ave
Baton Rouge, LA 70808

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The survey data used in this research came from Dr. Pamela Murray-Tuite's project NSF-CMMI-1822436, "Collaborative Research: CRISP Type 2: Coordinated, Behaviorally-Aware Recovery for Transportation and Power Disruptions."

Implementation Statement

DOTD Emergency Operations will be the primary end-users of this research, but other stakeholders who partner with DOTD Emergency Operations in responding to disasters are welcome to join future conversations. Close collaboration with these stakeholders is highly encouraged, with the goal of creating an academic-public partnership to test and improve this tool in practice.

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Introduction

Researchers from various disciplines have worked to estimate several evacuation demand models over the last decade [1]. Louisiana Transportation Research Center (LTRC) is one of the major research groups focused on evacuation demand modeling. All of the modeling components developed by LTRC were assembled in a computer package called "Hurricane Evacuation Modeling Package (HEMP)" between 2017 and 2020 [2]. HEMP allows the estimation of evacuation traffic depending on storm characteristics and decisions made by emergency managers. HEMP has been set up to operate in the New Orleans, Louisiana, metropolitan area and was tested using data from Hurricane Katrina in 2005. A graphic user interface was created to make HEMP easily accessible for emergency managers, who may not be familiar with the traffic simulation tools running in the background. Emergency managers are only asked to enter their decisions, such as phased evacuation orders, through the developed user interface. With other inputs provided in the background, HEMP automatically generates outputs, such as average travel time, to help emergency managers evaluate the impacts of their decisions.

This project was designed to test the HEMP computer package to evaluate and improve its accuracy, usefulness, and running time before it is released for practical use. The project team made the following improvements:

1. HEMP's input data was examined to ensure models were applied in the same way they were estimated.
2. Simulation outputs were compared with observed data, such as survey responses and traffic counts, to improve confidence in HEMP's prediction ability.
3. Several changes were made to improve HEMP's fitness for actual emergency management operations in Louisiana, such as the geographic unit receiving evacuation orders.
4. HEMP's computation speed was improved to provide reliable outputs in a shorter amount of time.

Additionally, this project sought to identify enhancements that could be made to further enable the HEMP computer package to support emergency management in Louisiana in an era with digital twins, which are "digital replicas of a physical object, person, system, or process, contextualized in a digital version of its environment" [3].

Literature Review

The following section first presents evacuation behavioral responses collected from household surveys conducted after major storms that affected southeast Louisiana, findings from past hurricane evacuation studies that discussed model transferability, and a discussion of if and how local demographics may change over the course of recurring disasters. The subsequent section presents content related to evacuation traffic simulations, including an explanation of the impacts of signal timing plans in such simulations and the importance of considering drivers' route choice behavior in disaster evacuation scenarios.

Simulating Hurricane Evacuation-Related Behavior

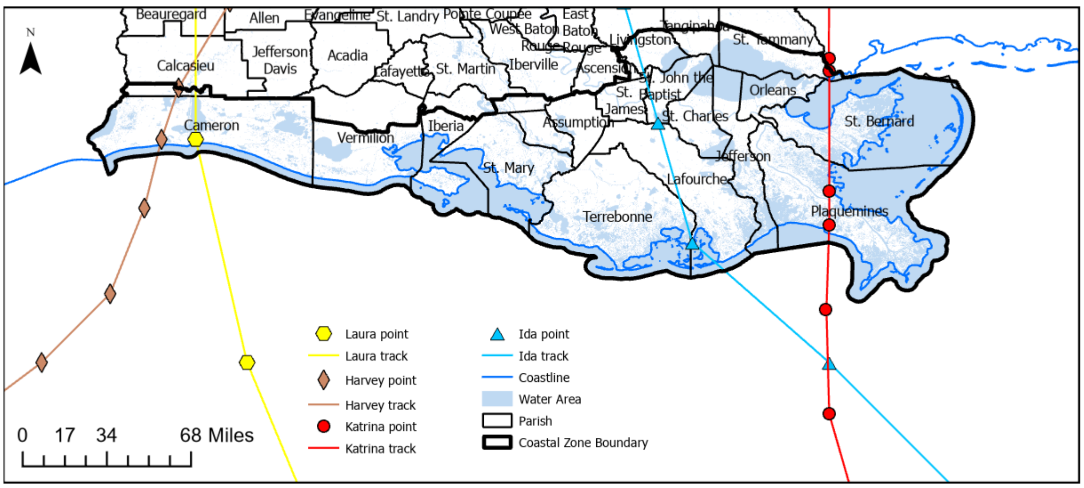
Past studies estimated statistical models based on survey responses to identify factors that influence the hurricane evacuation-related behavior of households to support evacuation simulation. These models illustrate that evacuation behavior is affected by both external conditions (e.g., storm intensity) and internal mechanisms (e.g., the risk value that the public assigns to storm intensity). If major external factors have been captured and internal choice mechanisms remain the same, the behavioral models estimated for one storm should perform well in predicting the evaluation behavior of households in a new storm setting [4]. This process is known as model transferability, which tests the stability of internal choice mechanisms within the population over various times and locations. Applying and transferring the estimated evacuation models to synthetic populations created for a region can help predict evacuation patterns, which are of vital importance to emergency management decisions, such as when and where to issue an evacuation order.

This project built upon past evacuation behavioral studies and identified what real-time information and value updates are needed for higher prediction accuracy. The set of evacuation-related behavioral models used in the current study included the evacuate/stay and departure timing joint choice models estimated using data collected after Hurricane Gustav [5]; the mode and accommodation choice models estimated using data collected after Hurricanes Irene, Sandy, and Gustav [4]; and the destination choice model estimated using data collected after Hurricane Floyd [6]. This set of models was applied because they aligned well with the study region characteristics and were integrated in a simulation framework developed for the study region of coastal Louisiana [2].

Post-Storm Behavioral Survey Responses

States on the U.S. Gulf Coast are frequently affected by tropical storms. Louisiana has experienced between $200-300 billion in economic losses due to tropical storms over the last 45 years [7], accounting for approximately 86% of the total economic loss from weather-related disasters during this timeframe. 38 tropical storms affected Louisiana between 2001 and 2021 [8]. Figure 1 shows several of the well-known billion-dollar storm events: Katrina (2005), Harvey (2017), Laura (2020), and Ida (2021).

Figure 1. Major hurricanes affecting Louisiana [8]



For some time, researchers have studied the evacuation-related choices made by households during hurricanes by conducting post-storm behavioral surveys. Table 1 presents responses collected from several such surveys. Hurricanes Katrina (2005) and Ida (2021) are two of the most devastating storms to strike southeast Louisiana over the past two decades. Hurricane Katrina made landfall as a Category 3 storm and resulted in severe storm surge, which led to a levee system failure in New Orleans [9]. Both Wu et al. [10] and Murray-Tuite et al. [11] studied survey responses collected after Hurricane Katrina. Table 1 presents statistics from responses that were collected from Louisiana only. Hurricane Ida (2021) made landfall in Louisiana as a Category 4 storm with 150-mph winds [12]. The data source for Hurricane Ida is a two-wave cross-sectional household behavioral survey conducted in 2021 with 1,369 responses [13]. Table 1 presents statistics from responses that were collected from a similar region as the post-Katrina survey, making the two data sets relatively comparable. Major observations reflecting the commonalities between the two surveys include:

1. Most respondents chose to evacuate one day before storm landfall.
2. Most respondents chose to evacuate using their own vehicle and go to friends' or relatives' homes.
3. Many respondents chose to evacuate using I-10 West toward Texas.

Evacuation patterns in the two storms did have several differences, including:

1. Early departure timing (i.e., 20% of respondents evacuated three days before storm landfall during Ida, but only 4% did so during Katrina)
2. Late departure timing (i.e., 13% of respondents evacuated on the day of storm landfall during Ida, but only 1% did so during Katrina)
3. Change in evacuation destination (i.e., more respondents evacuated using I-10 West toward Lake Charles and Houston, rather than north to Central Louisiana, during Ida than Katrina)

These changes in evacuation patterns could be due to the change in external conditions (e.g., storm characteristics) rather than internal choice mechanisms. The next subsection continues to review the model transferability of related studies in hurricane evacuation.

Table 1. Household evacuation behavioral statistics

	Katrina (2005)	**Ida (2021)**
Study area	Two coastal parishes in New Orleans-Metairie, Louisiana (Jefferson and St. Charles)	Seven coastal parishes in New Orleans-Metairie, Louisiana
Sample size	269	408
Evacuate/Stay		
Chose to evacuate	86%	68%
Evacuation timing		
3 days before landfall	4%	20%
2 days before landfall	44%	27%
1 day before landfall	51%	40%
On the day of landfall	1%	13%
Mode choice		
Own vehicle	89%	(na)
Ride with others	8%	(na)
Transit	1%	(na)
Other modes	2%	(na)
Accommodation choice		
Friends or relatives	61%	50%
Hotels/motels	18%	41%
Public shelters	3%	2%
Others	18%	7%
Destination choice		
New Orleans and nearby	10%	12%

	Katrina (2005)	Ida (2021)
Central/Northern LA	19%	4%
Baton Rouge, LA	12%	6%
Lafayette, LA	7%	2%
I-10 West (e.g., Lake Charles and Houston)	13%	25%
Other places/states	39%	52%

Note: ‘na’ means not available

Model Application and Transfer in Past Evacuation Simulations

HURREVAC (Hurricane Evacuation) is a situational awareness tool used widely among emergency managers in supporting their hurricane evacuation decision-making [14]. This tool brings forecasts from the National Hurricane Center (NHC) and evacuation clearance times from the Hurricane Evacuation Studies (HES) together in calculating evacuation decision time. Its latest web browser-based platform has been available since the 2020 hurricane season. In its current version, HURREVAC calculates evacuation timing by certain scenarios. Scenarios are defined by zones to evacuate, public response curve (i.e., fast, moderate, and slow), and seasonal populations (i.e., low, medium, high, and worst).

Research teams from different regions in the U.S. have been developing more advanced theoretical tools and frameworks to better predict evacuation travel, supporting public agencies’ decision-making. For example, Wolshon et al. applied agent-based traffic simulations in studying hurricane evacuation traffic in Louisiana [15]. The evacuation demand was generated based on the evacuate/stay decision model estimated by Gudishala and Wilmot [5]. The Gulf Coast TRANSIMS megaregion model was tested with data from Hurricanes Katrina (2005) and Gustav (2008) in assessing and evaluating traffic conditions under different storm conditions and traffic management strategies, such as phased evacuation orders and contraflow [15]. Murray-Tuite and Ukkusuri et al. also applied the agent-based modeling approach to simulate evacuation activities [16] [17] [18]. In 2017, they introduced an agent-based regional evacuation simulator coupled with user-enriched behavior called A-RESCUE, and they upgraded it in 2019 [19]. The simulator has two modules: household decision-making and traffic flow. Each household represents an agent making various evacuation-related decisions and pre-evacuation trips [17]. The household decision-making module communicates the timing, destination, and activity duration of each trip, which are then used as inputs in the traffic flow module. The traffic flow module uses an En-Route Route Choice Model, which is based on the k-shortest path routing algorithm, to simulate vehicle routing. The simulator utilized the Miami-Dade County, Florida, network as the testing scenario. More recently, Davidson et al. proposed an Integrated Scenario Ensemble-based evacuation (ISE) framework in 2020

[20] [21]. The hazard modeling portion of the framework considers the uncertainty in hurricane evolution and provides an ensemble of hurricane scenarios with inundation level and wind speed at each time step. The evacuation planning portion of the framework then solves a bi-level optimization problem. The objective is to minimize the number of people at risk and the expected evacuation travel time, which are performance evaluation statistics used in the framework. The higher-level problem is related to emergency managers' decisions whether or not to issue an evacuation order to a single zone or several zones at each time step. The lower-level problem is how households living in the study area make their decisions based on the given evacuation order. The following evacuation decision models were used by Davidson et al.: the evacuate/stay decision model estimated by Fu and Wilmot [22]; the accommodation choice model estimated by Mesa-Arango et al. [23]; and the DUE traffic assignment model [24]. Overall, the framework developed by Davidson et al. generates a tree of evacuation order recommendations to emergency managers. The theoretical framework is functioning and was tested in North Carolina with data from Hurricane Isabel (2003).

Some researchers paid attention to evacuation behavioral model transferability on a survey-to-survey basis. For example, Fu et al. [25] applied their evacuate/stay and departure timing choice models estimated with data collected after Hurricane Floyd (1999, South Carolina) in predicting the behavioral pattern for Hurricane Andrew (1992, Louisiana). The researchers tried to update the alternative specific constant in transferring their model to achieve higher prediction accuracy but found the improvement was marginal. Their research concluded that "applying the same distance function (followed a gamma distribution) to the two different hurricanes was a major source of error in model transfer," thus requiring further investigation. Gudishala and Wilmot [26] continued the research by transferring evacuate/stay and departure timing choice models estimated with data collected after Hurricane Gustav (2008, Louisiana) in predicting the behavioral pattern for Hurricane Andrew (1992, Louisiana). This study emphasized the importance of including time-dependent factors, such as time-of-day and distance function in a lognormal distribution, in an evacuate/stay model for better model transferability. Some past studies also tried to improve evacuate/stay model transferability by estimating a model with a pooled dataset, which included survey responses collected after multiple hurricanes [27].

Overall, the model transferability efforts detailed above were spent in applying the estimated models to predict patterns observed from a different survey. Past studies have not extended their model application to predict patterns observed from synthetic populations, which are created by year to test model transferability. This research fills in the gap and continues to answer how the estimated models could be further improved with minimum effort for higher prediction accuracy.

Population Migration in Responding to Natural Disasters

The purpose of creating synthetic populations for each year is related to population migration concerns. Population migration is common; therefore, local demographics change when researchers make year-to-year comparisons. For example, nearly eight million people in the U.S. moved between states in 2021; some of the already highly populated states on the Gulf Coast experienced significant population increases (e.g., Texas and Florida), while other states observed population declines (e.g., Louisiana) [28]. Within each state, work-from-home policies implemented since COVID-19 encouraged more people to move out of city centers [29].

In addition to the pandemic, natural disasters and climate change motivate people to migrate, either voluntarily or involuntarily. For example, Hurricane Katrina (2005) forced an estimated 277,000 Louisiana residents to relocate permanently [30]. Despite the recurring risk, some people still choose to return and continue living in a hazardous zone due to cultural, historical, and emotional reasons [31] [32]. Managed retreat is an emerging topic that discusses how to strategically and equitably mitigate negative community impacts caused by natural disasters [33]. Currently, there is no relocation planning performed at a regional scale since it requires significant planning efforts with community engagement and interagency collaboration. However, managed retreat has the potential to significantly change local demographics and thus influence disaster responses in the future.

Simulating Evacuation Traffic Patterns

As illustrated above, estimating evacuation-related choices can reveal whether people decide to evacuate, when they evacuate, where they go when they evacuate, and which travel mode they utilize during their evacuation. Each of these works aid in trip generation, mode choice, and trip distribution modules in the traditional four-step travel demand models. What remains is trip assignment onto road networks so that traffic impacts can be assessed. The following sections provide a review of previous traffic simulation studies that consider traffic signal timing plans and discuss drivers' route choice behavior in evacuation, both of which affect results from trip assignment.

Traffic Signal Timing Plan

Most studies focused on simulating the impacts of contraflow implemented on interstate highways and overlooked the impact of signal timing on local traffic during an evacuation [34]. Traffic signal timing plans can be modified when a mandatory evacuation order is issued. Traffic signals can be turned off, switched to flashing yellow, or manually controlled [35]. Several past studies have investigated and evaluated the impacts of various traffic signal timing plans in disaster scenarios. For example, Chen et al. [36] compared different signal timing strategies in facilitating evacuation in a no-notice disaster event by using a simulation model. Kolasani [37] used TransModeler to evaluate the evacuation efficiency of a network under two different traffic signal settings: flashing yellow/red signals and existing traffic signal plans. Kolasani [37] found that having flashing yellow signals on major evacuation routes and flashing red signals on minor cross streets is significantly better than maintaining current signal timing plans in terms of total delay per trip and average speeds.

Chang and Edara [38] proposed a reservation-based intersection control algorithm (AReBIC) for hurricane evacuation in a connected and autonomous vehicle (CAV) environment. The algorithm performed better than the next best optimal signal control on all operational measures, which decreased the total delay by 80%. However, there were still several practical issues, such as the delay and accuracy of communication. Ren et al. [39] proposed an integrated model to determine traffic flows on evacuation routes and traffic signal plans at intersections, based on the assumption that evacuation links are prepared for exclusive use by evacuees. They validated their model using the Sioux Falls network.

The efforts detailed above were spent in optimizing traffic signal timing plans for better evacuation productivity. They illustrate that signal timing plans should be considered and improved in evacuation traffic simulations for higher model fidelity.

Drivers' Route Choice Behavior

Route choice is a highly complex driver behavior. Drivers' route choices are likely to be influenced by several factors reflecting the characteristics of the driver, trip, and route. Driver attributes encompass personal characteristics such as age, gender, and income. Trip attributes may involve trip purpose and the chosen travel mode. Route attributes refer to features such as route length, travel speed, and the number of traffic signals [40]. Drivers may exhibit unexpected or irrational responses during an evacuation because of fear, panic, and stressful circumstances [1] [41]. Abdelgawad and Abdulhai [42] argued that drivers' stress and aggression would increase and lead to increased driver confusion and a higher occurrence of traffic incidents, such as breakdowns and collisions, during large-scale evacuations. Route choice behavior models developed in a disaster scenario in which drivers' perceptions of route characteristics and their ability to anticipate congestion or traffic conditions are taken into consideration [43]. Akbarzadeh's [44] hurricane evacuation route choice model incorporates four explanatory variables: route accessibility, route distance, perceived level of service on the route, and facility class of the route.

Traffic assignment methods in the simulation determine how the path costs are computed and how routes are assigned to each driver. Traffic assignment models typically incorporate the following factors: travel time, toll charges, travel delay due to congestion, travel distance, road condition, road safety, and the number of turns [45]. In traffic assignment, the user equilibrium (UE) approach, in which each driver minimizes their own travel time, requires knowledge of travel times on all network links, typically assumed to come from experience, which may be unrealistic during an evacuation [46]. Songchitruksa et al. [47] worked on alternative evacuation strategies using a dynamic traffic assignment model. Their study shows that the evacuation lanes on I-10 and US-290 in Texas can effectively manage high evacuation demand without implementing contraflow operations. Edara et al. [48] focused on modeling large-scale hurricane evacuations across 10 cities with approximately 2,000 miles of roadways in Virginia. They employed PTV Vissim as their microscopic traffic simulation tool. They considered lane-changing distance, average standstill distance, safe time headway, and speed oscillation as the parameters influencing driver behavior. Lv et al. [49] created a simulation model using TransWorld, an artificial transportation system platform, to assess how an individual's decisions regarding route selection affect the time it takes them to complete their evacuation. Moriarty et al. [50] assessed the effectiveness of specialized evacuation simulation tools like Oak Ridge Evacuation Modeling System (OREMS), Dynamic Network Evacuation (DYNEV), and Evacuation Traffic Information System (ETIS). They detailed the different characteristics and functionalities of these simulation tools. Chen et al. [51] used Simulation of Urban Mobility (SUMO) version 1.1.0 as the microscopic traffic simulator for two evacuation case studies in California.

Drivers' route choice behavior can be integrated into simulation-based traffic assignment models. Bonsall et al. [52] validated drivers' route choices based on specified origins and destinations using VLADIMIR (Variable Legend Assessment Device for Interactive

Measurement of Individual Route choice). They found that the VLADIMIR simulator could replicate actual route choices with high accuracy. Davis III [53] adopted Akbarzadeh's [44] route choice behavioral model in simulating hurricane evacuation traffic. He assessed the model's accuracy via TransModeler and compared the simulation with a route choice component against one using a shortest path approach. Dai et al. [54] built their simulation with SUMO to study driver route choice behavior in a connected vehicle environment and analyze how drivers' response to real-time traffic information could affect the performance of traffic system. Hu et al. [55] investigated dynamic route choice behavior in a mixed traffic flow condition with their simulation framework built in DynaTAIWAN. They found that the simulation-based dynamic traffic assignment procedure is capable of simulating multiple behavior rules and physical vehicle classes.

Objective

This project focused on testing the developed Hurricane Evacuation Modeling Package (HEMP) in a storm scenario different from those on which the models were based, thus observing and improving the performance of HEMP. The objectives of this project included:

- Improving and validating the prediction accuracy of the developed package
- Improving the package's fitness for actual emergency operations in Louisiana
- Improving the package's computational speed
- Exploring how to further enhance the package's capabilities

Scope

Figure 2 shows the scope and workflow of the entire project, with anticipation that the computer package could be utilized in real-time in the future. In this study, the project team assumed Hurricane Ida (2021) is an approaching hurricane, so that it can be examined and determined if and what additional information is needed to improve prediction accuracy.

For the evacuation behavior simulation:

- Step 1.1: Relevant input data, such as socio-demographics and storm tracks, were collected from different sources, while evacuation-related choice models were prepared for application and transfer.
- Step 1.2: Synthetic populations were generated by year from 2013 to 2022. The socio-demographic information needed as inputs for this project are not publicly available before 2013. Additionally, 2022 is the latest year that the needed socio-demographic information is available during the project time. This study tested applying the models on 1% and 10% synthetic populations. The team found that the predicted evacuation patterns were nearly the same after applying the corresponding weights.
- Step 1.3: Models were applied and transferred in a near-real-time fashion on the generated synthetic populations to simulate choices made by households under real world conditions.
- Step 1.4: The simulated choice behavioral results were compared with survey responses collected after Hurricane Ida (2021). An important assumption of the current study is that survey response samples are sufficient to reflect the choice patterns of the entire population.

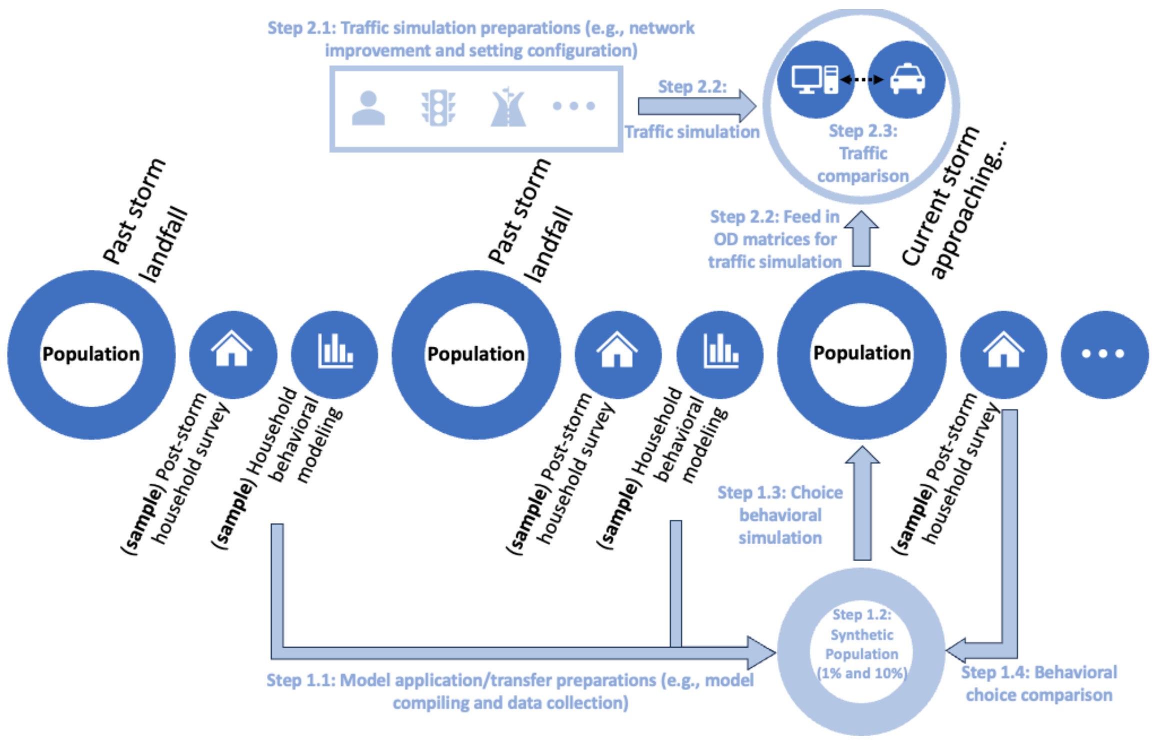
For the evacuation traffic simulation:

- Step 2.1: Relevant input data, such as the road network and traffic signal timing plan, were collected to build the traffic simulation environment, while drivers' route choice behavior parameters were set up in the simulation setting.
- Step 2.2: Traffic simulations were run in a near-real-time fashion with time-dependent Origin-Destination (OD) matrices generated from the evacuation-

behavior simulation process to understand traffic patterns on the virtual road network.

- Step 2.3: Sensors were created on the virtual road network as counters to record traffic volumes on certain road segments in the simulation. The virtual traffic volume was compared with traffic counts collected by loop detectors to investigate the performance of the created simulation environment.

Figure 2. Scope and workflow of the project



Note: Dark blue shows events in a time sequence in the real world. Light blue represents the work to create a digital twin supporting future storm responses.

Methodology

This section explains how evacuation choice simulation and evacuation traffic simulation were completed in this study. Hurricane Ida (2021) was utilized as the case to illustrate the study approach.

Simulating Evacuation-Related Choices

Data Overview

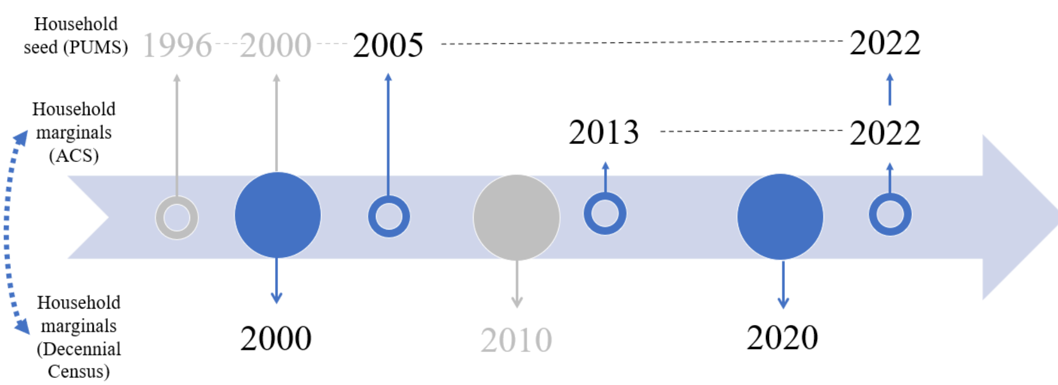
As shown in Figure 1, Hurricane Ida made landfall in southeast Louisiana. The New Orleans metropolitan area in this region is heavily populated and is thus likely to be affected by heavy traffic congestion during hurricane evacuation. Therefore, the study area for the current research included four coastal parishes in the metropolitan area: Jefferson, Orleans, Plaquemines, and St. Bernard.

Synthetic populations needed to be generated for the study area (i.e., Step 1.2 in Figure 2) for choice behavior simulation (i.e., Step 1.3 in Figure 2). Two datasets were needed to complete the generation: disaggregated household seeds (e.g., number of persons associated with a household) and marginal household statistics (e.g., number of households by household size in a geographic zone). Iterative Proportional Updating (IPU), one of the typical approaches applied in generating synthetic populations, was applied in this study [56].

Figure 3 presents data sources for the required data along with their availability by year. First, the Public Use Microdata Sample (PUMS) provided the following household seed data for synthetic population generation in this study: number of persons associated with a household record (NP) and number of vehicles available to a household record (VEH) [57]. The following data were also collected from the PUMS for behavioral model application in this study: household income (HINCP) and residential years (MV). Although the PUMS data is available as far back as 1996, the dataset does not include a unique ID for each Public Use Microdata Area (PUMA) until 2005.

Second, the American Community Survey (ACS) provided the following corresponding household marginal data for synthetic population generation in this study: household size and household vehicle ownership [58]. These data are available at the census tract level as far back as 2010 (see ACS Table B08201) but are available at the block group level only from 2013 onward (see ACS Table B11016 and Table B25044). Data at the block group level was preferred in this study to evaluate traffic at a more disaggregated scale. To fulfill this objective, decennial data was tested to serve as an alternative to provide household marginals at the block group level, but such data are only available for particular years (see Decennial Table H013 and Table H044) [59]. Ideally, household data from the same year as, or as close as possible to, the storm year should be collected and used in simulation. Overall, as of July 2024, existing census data at the block group level only allowed the simulation of evacuation behavior from 2013 to 2022.

Figure 3. Data sources and availability for creating synthetic populations



Note: Dashed straight lines indicate that datasets exist for consecutive years in between. Years and dashed lines colored in grey means certain data required in this study are missing from a corresponding dataset.

Table 2 is a summary of demographics and household marginals for the study area in particular years. The most significant change is the total number of people and households in the region, which declined approximately 25% between 2000 and 2010. However, these numbers increased approximately 10-14% between 2010 and 2013 and remained almost the same in 2021. Average household vehicle ownership increased approximately 12% between 2000 and 2010.

Examining the local demographics with a more disaggregated view, the number of census block groups shrank in the study region (i.e., 918, 902, and 842 in 2000, 2010/2013, and 2020/2021, respectively) when shifting the census zone boundaries. Table 3 visualizes the spatial distribution of household demographics over the years. Notable changes that can be observed from the map include:

1. Population density increased along I-10 in Jefferson Parish and New Orleans East

2. Average household size and vehicle ownership both grew in Uptown and Mid-City New Orleans from year to year.

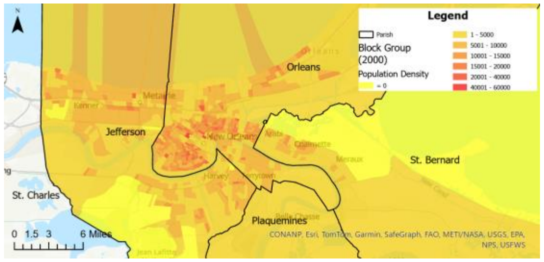
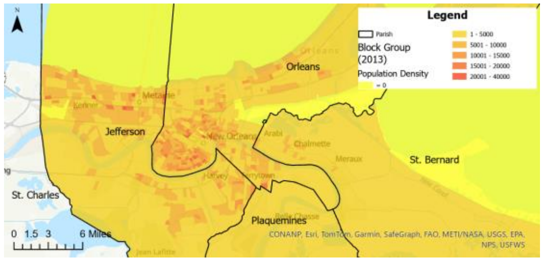
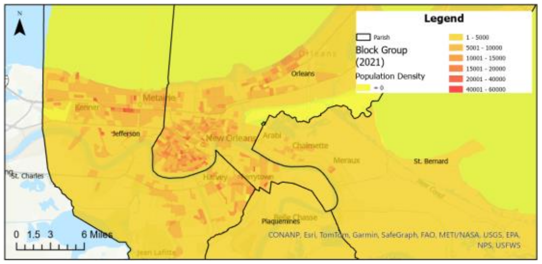
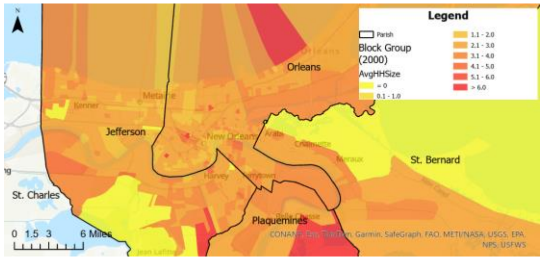
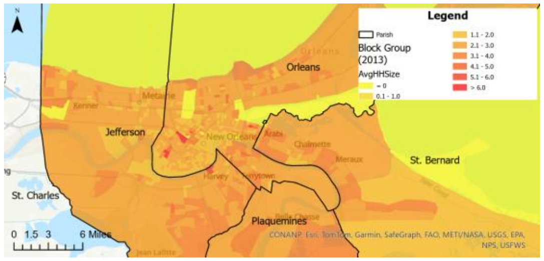
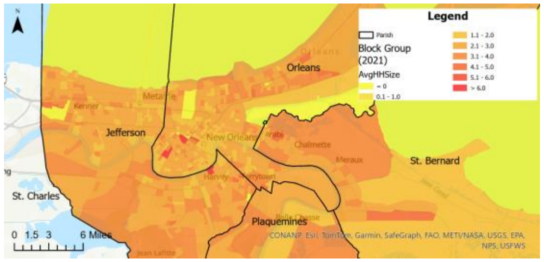
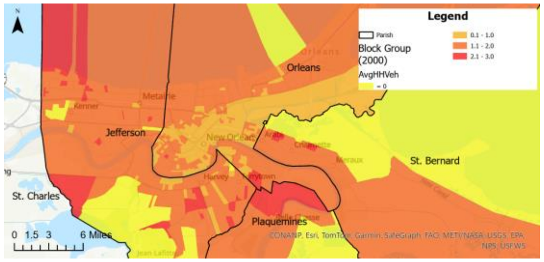
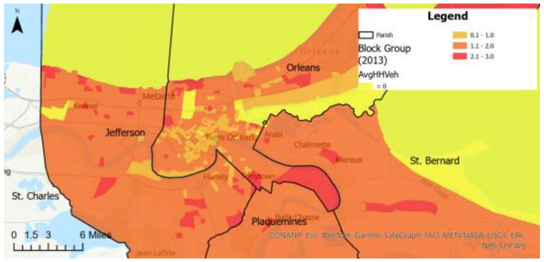
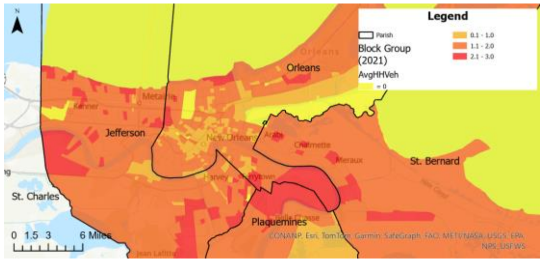
All of the observations indicate that local demographics have changed over the past several decades.

Table 2. Demographics and household marginals for the study area

Year	2000				2010				2013				2021			
Statistics	All	By block group			All	By block group			All	By block group			All	By block group		
		Range	Mean	Std Dev		Range	Mean	Std Dev		Range	Mean	Std Dev		Range	Mean	Std Dev
Total populations	1,034,126	[0, 6634]	1127	728	776,753	[0, 3929]	926	560	852,725	[0, 3905]	945	588	890,733	[0, 3571]	1058	573
Total households	398,629	[0, 2464]	434	265	297,532	[0, 1276]	369	214	337,978	[0, 1301]	375	216	355,051	[0, 1197]	422	212
Proportion of households by size																
1	0.29	[0, 1]	0.29	0.14	0.24	[0, 0.81]	0.31	0.12	0.28	[0, 0.92]	0.34	0.16	0.34	[0, 1]	0.39	0.18
2	0.29	[0, 1]	0.29	0.07	0.24	[0.07, 1]	0.31	0.06	0.26	[0, 1]	0.31	0.12	0.27	[0, 83]	0.31	0.13
3	0.18	[0, 0.34]	0.17	0.05	0.12	[0, 0.35]	0.17	0.05	0.14	[0, 0.80]	0.16	0.10	0.13	[0, 0.71]	0.14	0.10
4+	0.24	[0, 1]	0.24	0.11	0.15	[0, 0.59]	0.22	0.09	0.16	[0, 1]	0.19	0.12	0.15	[0, 0.68]	0.16	0.13
Average	2.59	[0, 173]	2.83	5.83	2.61	[1.33, 110.6]	2.65	3.67	2.52	[1.21, 148.4]	2.70	4.94	2.51	[1, 14.36]	2.55	0.92
Proportion of households by vehicle ownership																
0	0.18	[0, 1]	0.20	0.19	0.09	(na)	(na)	(na)	0.11	[0, 1]	0.15	0.16	0.11	[0, 0.88]	0.13	0.15
1	0.41	[0, 1]	0.40	0.12	0.30	(na)	(na)	(na)	0.36	[0, 1]	0.42	0.15	0.39	[0.03, 1]	0.43	0.17
2	0.32	[0, 1]	0.30	0.15	0.26	(na)	(na)	(na)	0.28	[0, 0.80]	0.31	0.16	0.29	[0, 0.82]	0.32	0.16
3+	0.09	[0, 1]	0.09	0.08	0.10	(na)	(na)	(na)	0.10	[0, 1]	0.12	0.11	0.11	[0, 0.71]	0.12	0.11
Average	1.33	[0, 3]	1.28	0.44	1.50	(na)	(na)	(na)	1.45	[0, 3]	1.40	0.42	1.45	[0.12, 2.58]	1.42	0.41

Note: ‘na’ means not available.

Table 3. Spatial distribution of household demographics across years

	2000	2013	2021
1			
2			
3			

Note: [1] Population density (per land square miles). [2] Average household size. [3] Average household vehicle ownership.

Please refer to the following link for the names of New Orleans neighborhoods: www.neworleans.com/plan/neighborhoods/

Model Application and Transfer

A focus of this study was to evaluate the transferability of models estimated beforehand and how the prediction results could be improved without collecting new survey data or estimating models for a new storm scenario (i.e., Step 1.3 in Figure 2). For the current study, Hurricane Ida was treated as an approaching storm; the survey responses collected after Hurricane Ida were used as a means for comparison (i.e., Step 1.4 in Figure 2). Note that such data does not exist before the storm landfall in an actual situation.

The following updates were made to align demographic years and geographic units. First, synthetic populations were generated with demographic files for each year, as described in the previous section. Second, origin and destination characteristics were collected for each year using the geographic unit required by each behavioral model. For example, data at the Zip Code Tabulation Area (ZCTA) level, such as the accessibility measures, are required as an input describing origin characteristics in the mode and accommodation choice model; data at the metropolitan/micropolitan level, such as the population in a destination, are required as an input describing destination characteristics in the destination choice model. This data was provided by the American Community Survey (ACS) [58]. Third, accommodation characteristics, such as hotel daily rate and occupancy rate, were collected for each year using the geographic unit required by each behavioral model. Data sources included the County Business Pattern [60] and Statista [61]. A geographic unit crosswalk file was created using the Spatial Join operation (i.e., “largest overlap”) in ArcGIS to align the various geographic units used in the process. Finally, because the models include income-related variables, the inflation rate is considered and accounted for in a way that updates scale parameters for model transferability. With all of these data preparations, this software package can be used to support evacuation operation drills with storms that occurred from 2013 to 2022.

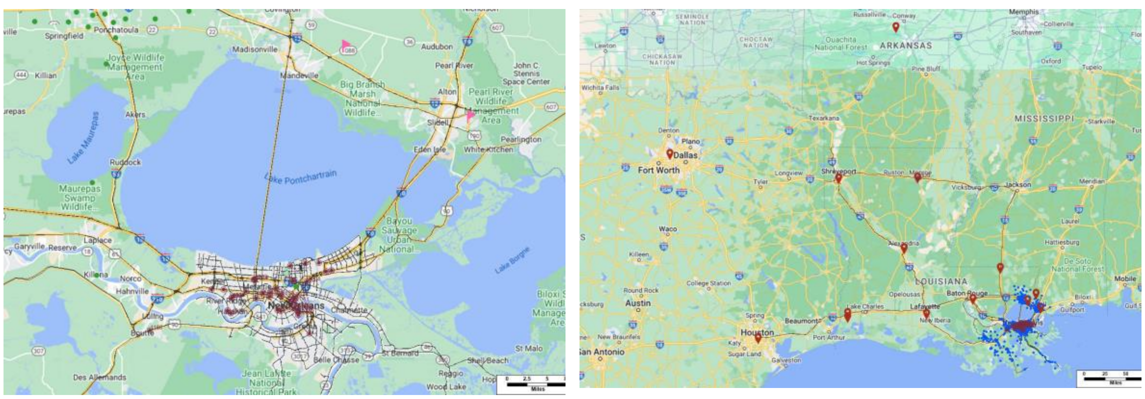
The Discussion of Results section provides further detail on how the evacuation choice simulation work in TransCAD could be further improved by observing the simulation results.

Simulating Evacuation Traffic Patterns

The evacuation demand estimation output from TransCAD is a series of time-dependent OD matrices. The matrix outputs from TransCAD serve as the input for evacuation traffic simulation in TransModeler. This study continued with Hurricane Ida (2021) as the case and focused on the 72 hour period prior to storm landfall as the traffic simulation period. The project team improved the simulation environment, including road network improvement and signal timing plan integration, and created a set of simulation scenarios to identify the group of parameters that best reflected drivers' route choice behavior during the Hurricane Ida evacuation.

Figure 4(a) shows the simulation road network with a zoom-in view on the New Orleans metropolitan area, which includes primary local roads and interstate highways. Figure 4(b) shows the entire simulation road networks with a regional view. The blue dots represent the 1,143 trip origins that are within the New Orleans area. The red location marks represent the 14 major hurricane evacuation destinations that are within and outside Louisiana.

Figure 4. Road networks in the study



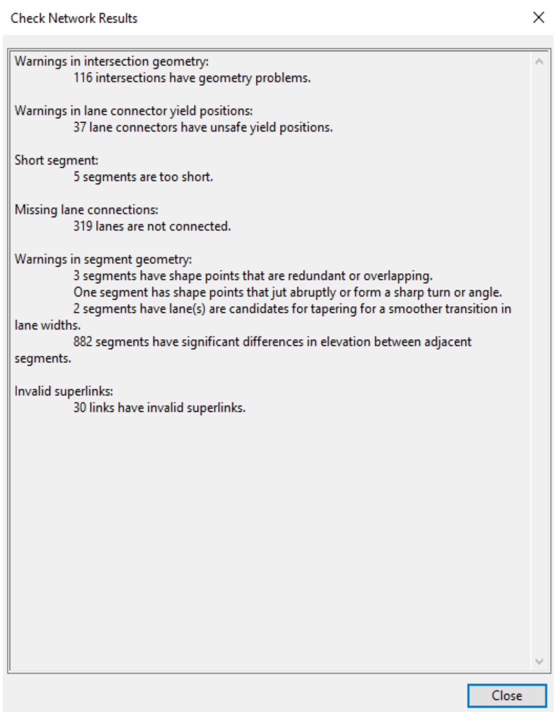
(a) New Orleans Networks (Zoom-In View)

(b) Regional Networks (Zoom-Out View)

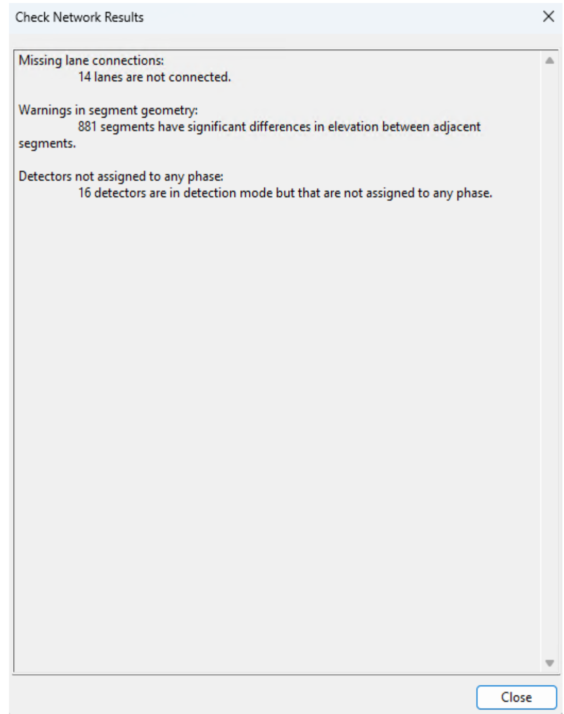
Road Network

In TransModeler, traffic network cleanup consists of checking the simulation database for errors and making corrections based on previous work in the Hurricane Evacuation Modeling Package (HEMP). This process includes identifying and correcting lane connection issues, roadway geometry issues, intersection geometry issues, etc. Figure 5 is a summary of improvements made during the project time by running the "Error Checking–Check Network" in TransModeler. The remaining warnings about elevations and detectors will not affect simulation outputs in this study according to the TransModeler user manual. The remaining issue of missing lane connections could not be further corrected after making multiple attempts.

Figure 5. Road network improvements



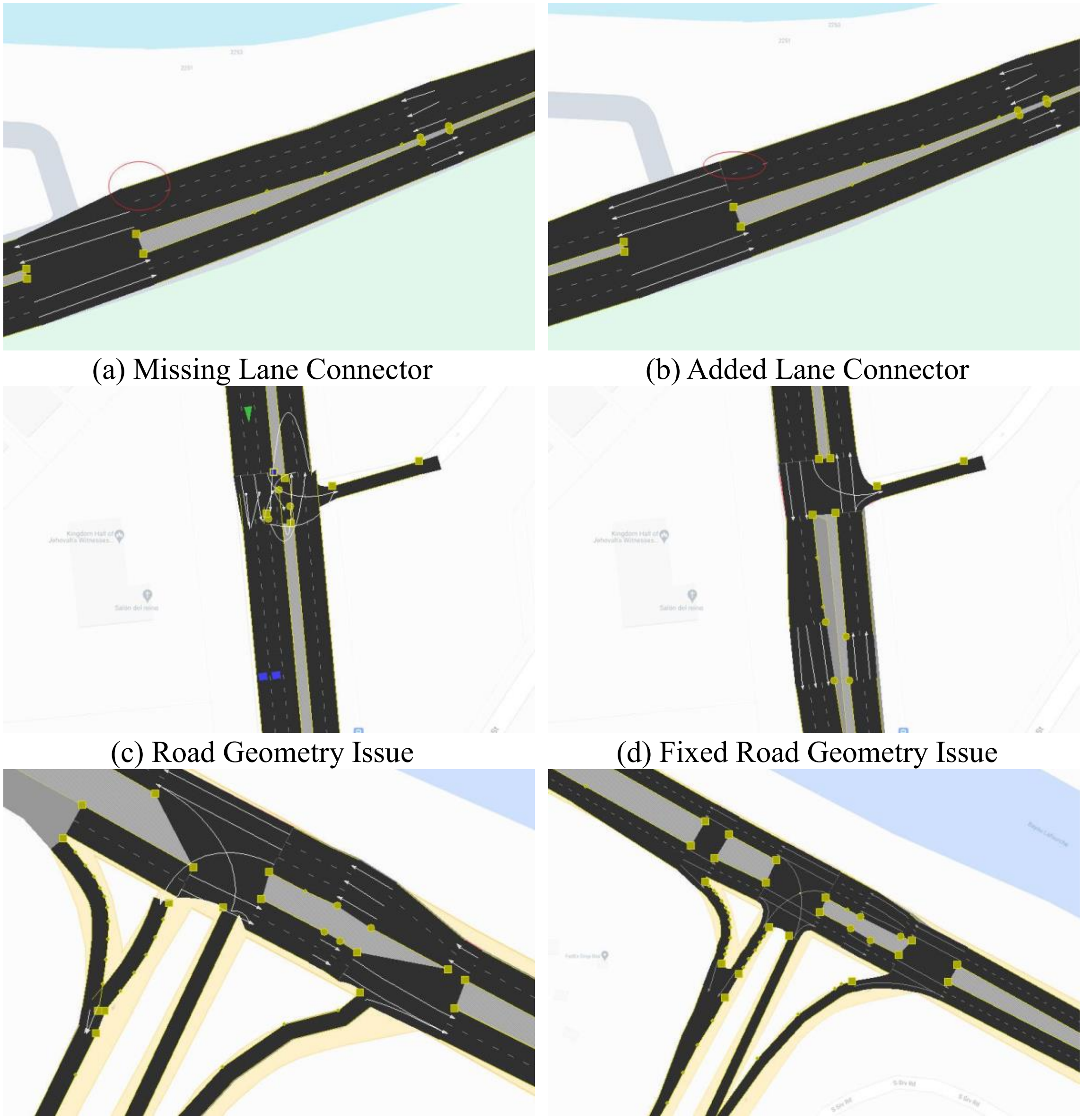
(a) Before network improvements



(b) After network improvements

Figure 6(a), (c), and (e) provide examples that illustrate three typical issues. Figure 6(b), (d), and (f) show how these issues were resolved. These corrections ensure a more accurate representation of the physical road network. The simulation accuracy and productivity are expected to improve due to the updates.

Figure 6. Road network issues and corrections



(a) Missing Lane Connector

(b) Added Lane Connector

(c) Road Geometry Issue

(d) Fixed Road Geometry Issue

(e) Intersection Geometry Issue

(f) Fixed Intersection Geometry Issue

Signal Timing Plan

Traffic signal timing plan information was obtained from various sources, ranging from hard copies of traffic signal inventory plans from a local district of the Louisiana Department of Transportation and Development (DOTD), to Synchro™ network timing plans in Comma Separated Value (.csv) format from two local transportation consulting agencies, Neel-Schaffer and Urban Systems Inc. DOTD provided traffic signal plans for approximately 299 intersections in the New Orleans area. Of these sites, approximately

253 intersections had complete and valid traffic signal timing plans, while the remainder were empty, updated, or unable to be used due to construction. Approximately 150 Synchro-coded timing plans along six different stretches in the New Orleans area were obtained from Neel-Schaffer and Urban Systems Inc. Therefore, there were a total of 403 valid signal timing plans. However, there were 525 major intersections on the road network created in TransModeler, which means 122 intersections along the major evacuation routes had missing signal timing information in the latest version [37].

TransModeler allows users to code six built-in intersection control types: None, Stop or Yield, Pretimed (Sequential Phasing), Pretimed (Concurrent Phasing), Pretimed Signal Group, and Traffic Actuated. Therefore, all of the intersections must be categorized and coded with one of the six available options. TransModeler also allows traffic signals at an intersection to switch between different control plans based on the time of day. For instance, traffic signal plans operate as Pretimed during peak hours and Traffic Actuated during off-peak periods at some intersections. The 122 intersections with missing signal timing plans are manually coded as having Pretimed (Concurrent Phasing) signals based on observed traffic volume and nearby intersection setup. After assigning proper intersection controls, the final signal timing plan file created for this simulation work included 339 Pretimed signals and 186 Actuated signals [2] [37].

Additionally, some of the traffic signal timing plans had internal errors that needed to be corrected. Errors included no signal assignments, invalid plans, incorrect signal state assignments, etc. All of the errors were corrected before running the simulation.

Route Choice Scenario

As discussed in the Literature Review section, drivers' route choice behavior is influenced by a wide range of factors. This project continued to investigate how to integrate those factors into evacuation traffic simulation and how to set up those factor values to obtain the simulated traffic best fit observed in reality. TransModeler is capable of simulating route choice by using either the deterministic/stochastic shortest path-based models or the probabilistic logit-based model. Additionally, there are parameters that can determine when drivers will consider new paths when they are en route. Various route choice parameters can be adjusted depending on the selected route choice method [62]. Table 4 shows a combination of 20 route choice testing scenarios in this study, which are defined by the minimize item, the shortest path model, and the percentage of informed drivers. The route choice method in TransModeler can be set up in the Project Settings, where various route choice parameters can be applied depending on the selected route choice method.

Table 4. Route choice testing scenarios

Scenario	Minimize item	Shortest path model	%Informed drivers
1~5	Travel time	Deterministic	10%, 30%, 50%, 70% and 90%
6~10	Travel time	Stochastic	10%, 30%, 50%, 70% and 90%
11~15	Generalized cost	Deterministic	10%, 30%, 50%, 70% and 90%
16~20	Generalized cost	Stochastic	10%, 30%, 50%, 70% and 90%

Minimize items. The minimize item option allows users to select whether to minimize travel time or generalized cost. If generalized cost is selected, path costs can be defined by travel times, turning delays, tolls, and other user-defined variables, which allows more factors to be considered in simulating drivers' route choice [43] [63]. The perception of these costs can also vary from driver to driver and depend on a variety of driver characteristics, including access to traveler information. One or more driver groups can be defined in the route choice model parameter setting so that route choice behavior can vary among drivers.

Path costs can also be defined by roadway classification, which is a significant factor in influencing route choice during a hurricane evacuation. The cost coefficient value for roadway classification is derived based on the model estimated by Akbarzadeh [44]. The negative coefficient means interstate highways have lower path costs, which should be preferred by drivers in their evacuation route choice. It is also notable that generalized cost only works with the shortest path models, not in the probabilistic logit-based models.

Shortest path models. TransModeler is a path-based simulation tool, which can generate a set of alternative paths for a vehicle or driver based on predetermined inputs or route assignment models [62]. Drivers traveling between the same origin-destination (OD) pair are not likely to follow the same path. Additionally, drivers may not choose the path with the minimum cost. There are two shortest path-based route assignment models: deterministic shortest path and stochastic shortest path [64].

The deterministic shortest path is the simplest method; all vehicles follow the absolute shortest path. Based on past research, this method should only be used on an experimental basis or for small networks, where there is little or no variation in the available paths drivers may choose between any given origin-destination pair [65]. This traffic assignment model is included here for testing purposes [64]. The stochastic shortest path method is like the deterministic shortest path in that all vehicles choose the shortest path. However, path costs are randomized for each individual vehicle to account for variations in perception and/or choice behavior. As a result, there will be multiple shortest paths for a given origin-destination pair [63] [65].

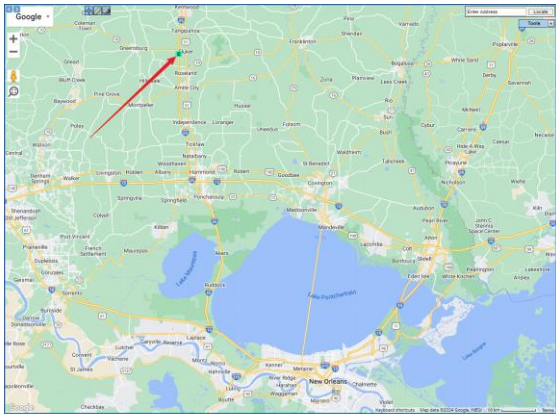
Informed drivers. Informed drivers refer to the percentage of drivers in the group that have access to updated travel time information, such as traffic congestion, crashes, and roadwork. This information helps drivers choose the fastest or least congested route. Based on a 2020 Statista survey [66], not all smartphone users utilize navigation apps on their smartphone during their travels. Additionally, some drivers do not have a smartphone or an in-vehicle navigation system. All of these facts mean that the percentage of informed drivers is an unknown value that needs to be tested. This parameter must also be tested in the future as the percentage of autonomous vehicles increases.

Creating Virtual Sensors for Traffic Count Comparison

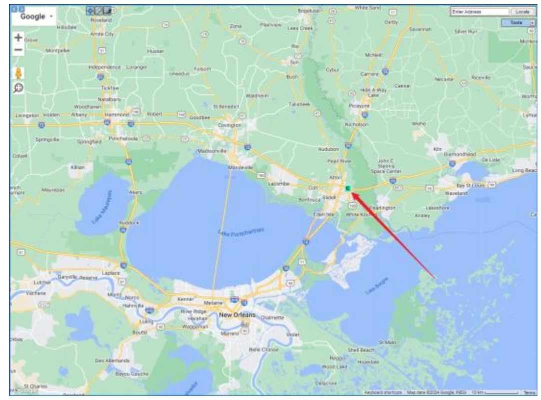
Only a handful of loop detectors provide continuous traffic observations in Louisiana, and some of them have missing traffic count data for the study period of August 2021. This study was only able to extract traffic count data from four loop detectors to serve as the ground-truth data for simulation comparisons. The four loop detectors are 015-NB (I-55N), 067-EB (I-10E), 063-WB (I-10W), 008-WB (US-90W), as shown in Figure 7. All of the routes are major hurricane evacuation routes, so the comparison was of great value for this study.

The hourly traffic volume in both directions can be obtained from those loop detectors. The landfall time of Hurricane Ida was 11:55am on Sunday, August 29, 2021. The project team found that traffic count data was not provided after 6:00am on August 29. Therefore, this study collected and used traffic count data from 6:00am on Thursday, August 26 until 6:00am on Sunday, August 29; this was the 72 hour period used for traffic comparison. The average hourly traffic volume in the 72 hour period for the four locations was 851 on I-55N, 1446 on I-10E, 1645 on I-10W, and 769 on US-90W. Virtual sensors needed to be created and placed on the simulation road network in TransModeler to match the loop detector locations for simulation accuracy evaluation. After each simulation run, sensor data were saved in "detector.bin" files. Embedded code was written with the GIS Developer's Kit (GISDK) to process the sensor data automatically and generate a report to compare with the traffic counts collected from loop detectors. The corresponding sensor IDs in TransModeler were 2682, 2685, 2880, and 2882.

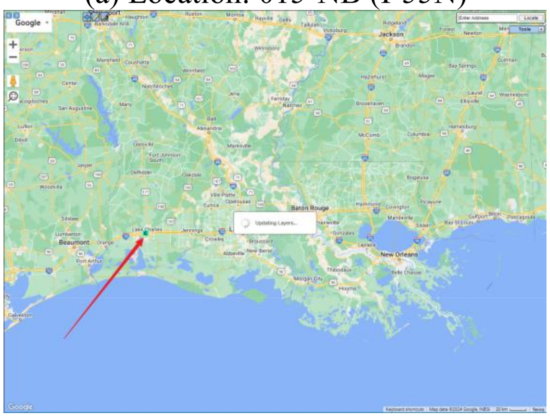
Figure 7. Location of loop detectors



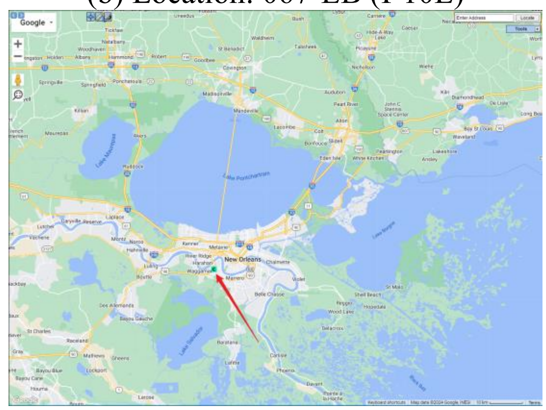
(a) Location: 015-NB (I-55N)



(b) Location: 067-EB (I-10E)



(c) Location: 063-WB (I-10W)



(d) Location: 008-WB (US-90W)

Simulation Experiment

The evacuation choice simulation in TransCAD generated 12 Origin-Destination (OD) matrices, which served as the input for traffic simulation work in TransModeler. The 12 OD matrices reflected evacuation traffic patterns over the 72 hour period prior to Hurricane Ida's landfall. One cell in an OD matrix represented the demand, or traffic volume, between an OD pair in a time period of 6 hours. However, TransModeler requires time-dependent OD demand in an hourly interval. Therefore, GISDK code written in TransModeler distributed the 6 hour demands from above to each hour using a simple curve fitting method [2]. TransModeler then ran the entire 72 simulation hours using the defined road networks, a created traffic signal timing plan, and a selected set of route choice parameters.

It should be noted that the OD matrices only record evacuation traffic. However, not all people living in the New Orleans metropolitan area evacuated; they may have traveled for other purposes, such as stocking food for storm preparations before storm landfall.

Therefore, it made sense to consider background traffic together with the evacuation simulation results in comparison with the traffic count data collected from loop detectors. In this study, background traffic data for the same 72 hour interval in the previous week was used as a proxy; background traffic data was collected from the four loop detectors from 6:00am on Thursday, August 19 until 6:00am on Sunday, August 22. In the next stage, near-real-time traffic information could be connected to the computer package to serve as an input source.

This study used a variety of statistics in comparing the simulated traffic counts against the observed traffic counts. This study used Mean Squared Error (MSE) and scenario ranking to assist in result discussions. Additionally, both hourly and 6 hour traffic distributions were evaluated to identify the best set of drivers' route choice parameters.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - p_i)^2$$

where,
y_i is the observed traffic flow collected from loop detectors,
p_i is the predicted traffic flow in TransModeler with background traffic considered, and
n is 72 in the hourly comparison and becomes 12 in the 6 hour comparison.

Discussion of Results

All of the behavioral models were compiled with required input datasets as one integrated software package in TransCAD and TransModeler, which allows factors such as storm intensity, storm position and path, time of day, land use, population characteristics, network conditions, and management operation decisions to play a role in simulating evacuation behavior and traffic [2]. The matrix outputs from TransCAD served as the inputs for evacuation traffic simulation in TransModeler. User interfaces were developed and integrated in the software package so that even those with little knowledge of simulation tools can run the program. The input needed from users is solely related to evacuation management operation decisions, such as when and where to issue an evacuation order.

The simulation was run on a high-performance device with the following specifications: processor (Intel (R) Core (TM) i9-14900KF 3.20 GHz), RAM (64.0 GB), GPU (NVIDIA GeForce RTX 4090), and system (64-bit operating system, x64-based processor). First, the computational speed of HEMP was significantly improved in TransCAD 9.0 by optimizing the structure of data and code, reducing overhead running time (e.g., generating a full set of synthetic populations ahead of time), and simplifying calculation steps. After these changes, simulating the evacuation choices of 1% of the populations in TransCAD took only five minutes. If 10% of the populations were simulated, the running time increased to 25 minutes. This study found no difference in comparing the results generated from the two scenarios (i.e., 1% vs 10%) since weights were properly applied. Second, the computational speed of HEMP was improved by using TransModeler 7.0 instead of TransModeler 5.0 and setting the macroscopic vehicle state step size to the maximum value of 300s and the vehicle position step size to the maximum value of 30s. With all of these updates, simulating traffic patterns for the 72 hour period took approximately 110 minutes, including the time to generate simulation summary reports and graphics. Overall, the amount of time to complete an entire HEMP simulation cycle was approximately 2 hours, which was much improved from the previous version, which took 4 hours. The simulation time could possibly be further reduced on higher-performing devices.

Predicting Hurricane Evacuation-Related Behavior

This section focuses on improving the evacuation demand estimation outputs from TransCAD. The simulation replicated management decisions made during Hurricane Ida to best reflect the real world conditions. Table 5 shows the results of the major simulation tests that were conducted. Results were improved from one simulation to the next on its right.

Table 5. Simulation test results

	Survey responses [13]	**Simulation (with inflation accounted)** (Baseline)	**Simulation (with lognormal update: 1)**	**Simulation (with lognormal update: 2)**	**Simulation (update destination attributes)**
Evacuate/Stay					
Chose to evacuate	49%	52% (+3%)	47% (-2%)	44% (-5%)	44% (-5%)
Evacuation timing					
3 days before landfall	20%	10% (-10%)	13% (-7%)	16% (-4%)	16% (-4%)
2 days before landfall	27%	18% (-9%)	24% (-3%)	28% (1%)	28% (1%)
1 day before landfall	40%	52% (+12%)	49% (+9%)	44% (4%)	44% (4%)
On the day of landfall	13%	20% (+7%)	14% (+1%)	12% (-1%)	12% (-1%)
Mode choice (*)					
Own vehicle	89%	(-)	(-)	90% (+1%)	90% (+1%)
Ride with others	8%	(-)	(-)	6% (-2%)	6% (-2%)
Transit	1%	(-)	(-)	2% (+1%)	2% (+1%)
Other modes	2%	(-)	(-)	2% (0%)	2% (0%)
Accommodation choice					
Friends or relatives	50%	(-)	(-)	56% (+6%)	56% (+6%)
Hotels/motels	41%	(-)	(-)	36% (-5%)	36% (-5%)
Public shelters	2%	(-)	(-)	2% (0%)	2% (0%)
Others	7%	(-)	(-)	6% (-1%)	6% (-1%)
Destination choice					
New Orleans and Nearby	12%	(-)	(-)	8% (-4%)	4% (-8%)
Central/Northern LA	4%	(-)	(-)	12% (+8%)	8% (+4%)
Baton Rouge, LA	6%	(-)	(-)	13% (+7%)	8% (+2%)
Lafayette, LA	2%	(-)	(-)	6% (+4%)	4% (+2%)
I-10 West (e.g., Lake Charles and Houston)	25%	(-)	(-)	24% (-1%)	30% (+5%)
Other places/states	51%	(-)	(-)	37% (-14%)	46% (-5%)

Note: "(NUMBER%)" presents the difference in comparing the survey responses. "(*)" the survey data was the average based on responses collected in previous hurricanes to serve as a comparison. "(-)" results are not reported due to imprecise outputs from models applied in previous steps. Shaded cells indicate that the absolute difference is over 5%.

Improve Predictions of Evacuation Rate and Departure Timing

The next two sections explain how the simulation results shown in Table 5 were improved from the baseline results, shown in the third column from the left. Evacuation rate and departure timing prediction needed to be studied first. Otherwise, prediction errors would propagate as additional models are applied. This study chose a ±5% difference from the survey response distribution pattern as the criterion for satisfactory model application/transfer.

First, updating alternative specific constants in the sequential logit model estimated by Gudishala and Wilmot [5] did not help improve the prediction of evacuate/stay and departure timing choices, which was similar to the findings of Fu et al. [25]. Results were not presented in Table 4 due to reduced model transfer performance.

Second, the major error source was the distance between the study area and the approaching storm, which was transformed by a lognormal distribution in the model estimated by Gudishala and Wilmot [5]. This finding is also similar to that of Fu et al. [25]. After looking into the issue, it was found that the lognormal distribution parameters, mu and sigma, should be both time-dependent and distance-sensitive. The following text explains how to calibrate lognormal distribution parameters based on the characteristics of an approaching storm for higher prediction accuracy.

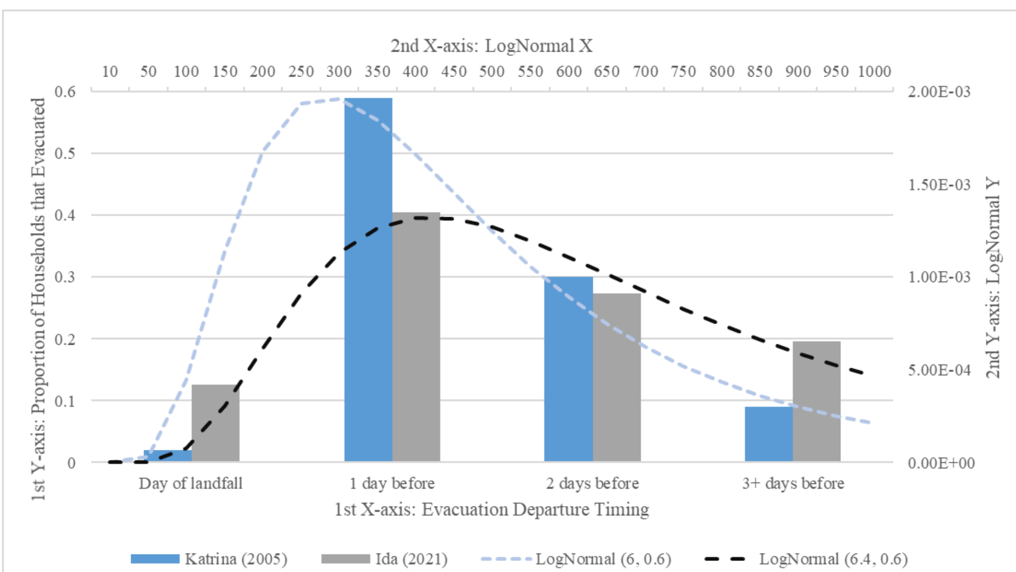
Figure 8(a) shows the proportion of people who evacuated by day based on observations from surveys (see Table 1). Hurricane Katrina was used for comparison and approach illustration purposes. More households evacuated three days before the storm landfall and on the day of storm landfall during Ida, while more households evacuated one day before storm landfall during Katrina. Clearly, two different lognormal curves should fit the two storms. Therefore, the parameters of lognormal distributions needed to be updated for each case. The fourth column from the left (i.e., “Simulation (with lognormal update: 1)”) in Table 5 shows the simulation results by using the parameters marked in Figure 8(a) for Ida. Note that the simulation results were much improved compared to the baseline but were not sufficient to be within a ±5% difference of the survey responses.

Further investigation showed that Hurricane Katrina was approximately 350 miles away from New Orleans one day before its landfall. However, Hurricane Ida was 550 miles away from New Orleans one day before its landfall. This observation made aligning the two storms in Figure 8(a) on a same distance scale (i.e., the second X-axis) problematic. Figure 8(b) illustrates how the lognormal distribution would be different when the distance scale is updated for Hurricane Ida. The two black dashed lines in Figure 8(a) and Figure 8(b) use the same lognormal parameters to assist in the comparison. Clearly, the lognormal distribution needs to be shifted by updating the distribution parameters mu and sigma. The fifth column from the left (i.e., “Simulation (with lognormal update: 2)”) in Table 5 shows the simulation results by using the parameters marked for the dotted line in Figure 8(b). The simulation results were much improved over “Simulation (with lognormal update: 1)” and met the ±5% difference criterion.

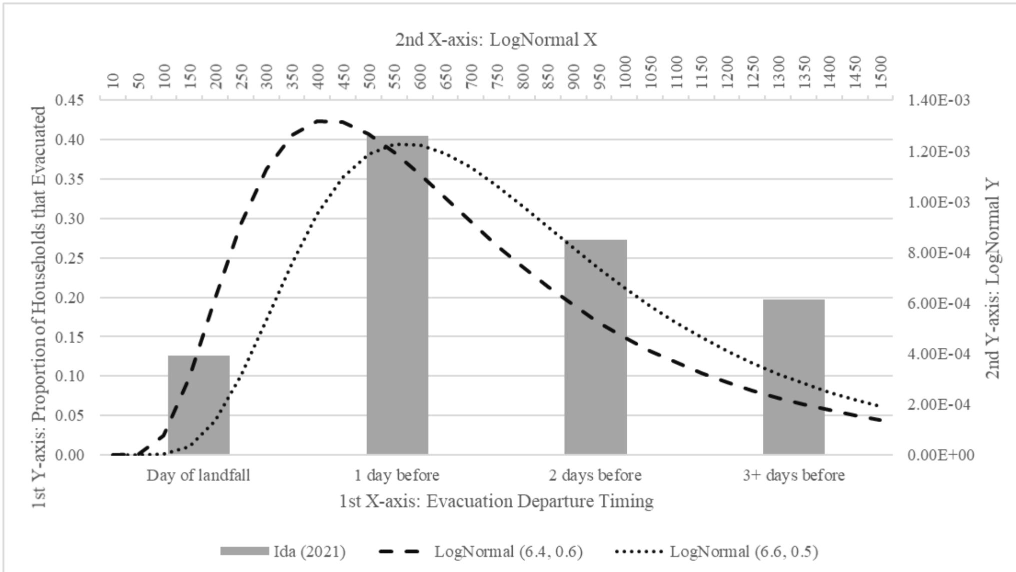
This finding illustrates that evacuation rate and departure timing should be predicted in real time, using the storm forecast as an input. The location and scale parameters in the lognormal distribution are both time- and distance-dependent, which can be updated based on real-time storm activity forecast feeds. This also explains why and how two different sets of location and scale parameters were applied in the lognormal distribution in two previous studies for model performance improvements (i.e., (6, 0.6) in [3] and (6, 0.1) in [26]).

Figure 8. Evacuation proportion and lognormal distribution

(a) For two hurricanes (i.e., lognormal update: 1)



(b) For Hurricane Ida (i.e., lognormal update: 2)



Improve Evacuation Logistics Prediction

In Table 5, the accommodation choice model overestimated the proportion of households choosing friends' or relatives' homes as their accommodation; the error rate is 6%. The destination choice model overestimated the proportion of households choosing Baton Rouge and Central/North Louisiana (e.g., Alexandria, Shreveport, and Monroe) as their destinations, while it underestimated those choosing other out-of-state places as their destinations. The over-/under-estimations could be due to Hurricane Ida initially being predicted to hit the Baton Rouge area directly, which made the Baton Rouge area an unsafe destination. Hurricane Ida also induced widespread and long-duration power outages in Louisiana [67]. Both conditions could make Baton Rouge and other in-state destinations less favorable as evacuation destinations. This observation reveals the importance of updating the risk perception factor values, such as DANGER, for the destination choice model and that such factor value updates should take the preliminary hurricane track into consideration, rather than relying only on the best hurricane track. As a test, this research marked all the destinations in Louisiana as at risk (i.e., DANGER = 1). Such changes improved the simulation results, as shown in the last column in Table 5. Though the number of people choosing to stay in New Orleans and nearby places was underestimated, this may not be a negative for evacuation management, since traffic impacts on interstate routes would not be underestimated.

Predicting Evacuation Traffic Patterns

As shown in Table 4, 20 scenarios were tested to look for parameters that would allow the model to best match the traffic flow observed during Hurricane Ida. The simulation ranges from Thursday, August 26, 2021 at 6:00am until Sunday, August 29, 2021 at 6:00am.

Figure 9 and Figure 10, along with Table 6 andTable 7, include the following abbreviations for simplicity:

1. T: Minimize Travel Time
2. G: Minimize Generalized Cost
3. D: Deterministic Shortest Path Model
4. S: Stochastic Shortest Path Model.

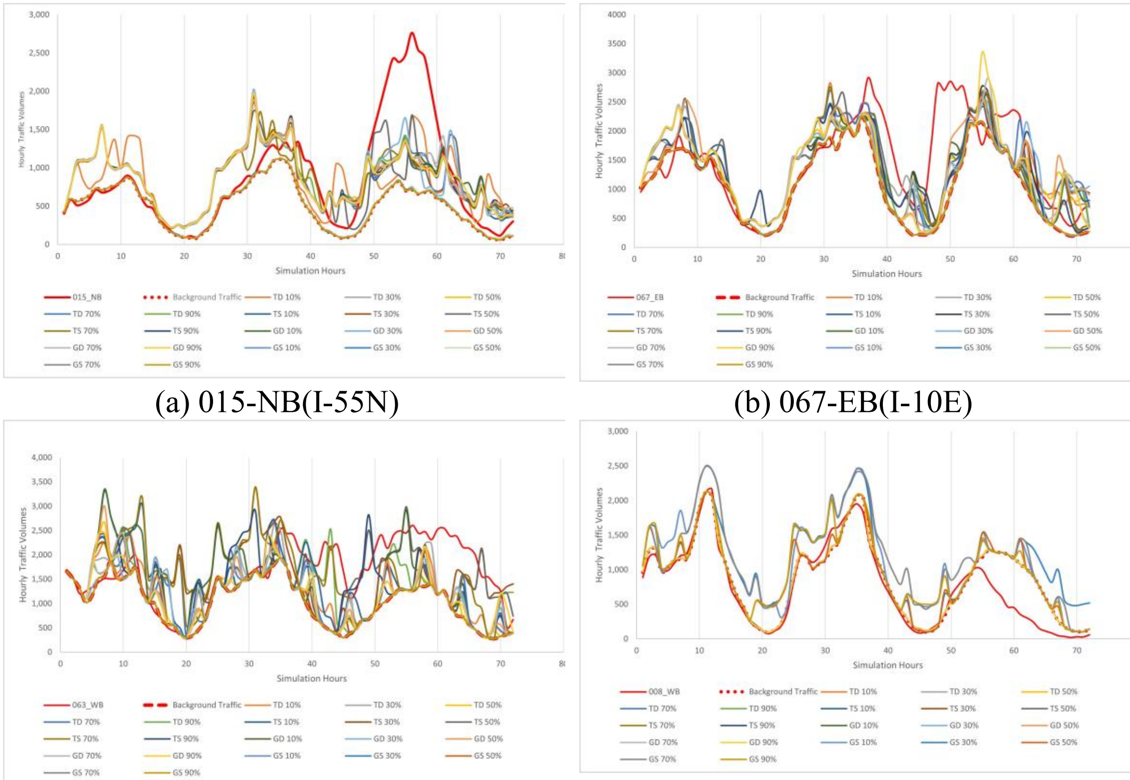
The percentage values refer to the percentage of informed drivers (InfDr). For example, TD10% represents the scenario of minimizing travel time in the deterministic shortest path model with 10% informed drivers.

Figure 9 shows hourly traffic flow comparison between loop detectors and simulation runs for all of the testing scenarios. The charts in Figure 9 show multiple peaks and troughs, indicating a cyclical pattern of traffic volumes. Peaks occur near 10, 35, and 55 hours, which correspond to morning hours. Troughs occur near 20, 45, and 70 hours, which correspond to nighttime hours.

It should be noted that traffic volumes are significantly higher than background traffic, which is the traffic volume collected from the previous week, after 48 hours. This may indicate that more traffic is for evacuation purposes after 48 hours, or 22 hours before storm landfall. This observation is especially true for routes I-55N, I-10E, and I-10W. There is less traffic on US-90W in the last 15 hours, perhaps because US-90W is closer to the coastline and therefore a higher travel risk.

It should also be noted that traffic counts from the loop detector are very close to the background traffic flow in the first 30 hours, or 40 hours before storm landfall. This indicates that evacuation traffic may only contribute marginally to the total traffic in the first 30 hours of the simulation. All of the observations match previous findings that people are less likely to evacuate during nighttime hours and that more people would like to evacuate one day before storm landfall.

Figure 9. Comparison of hourly traffic volumes



(a) 015-NB(I-55N)

(b) 067-EB(I-10E)

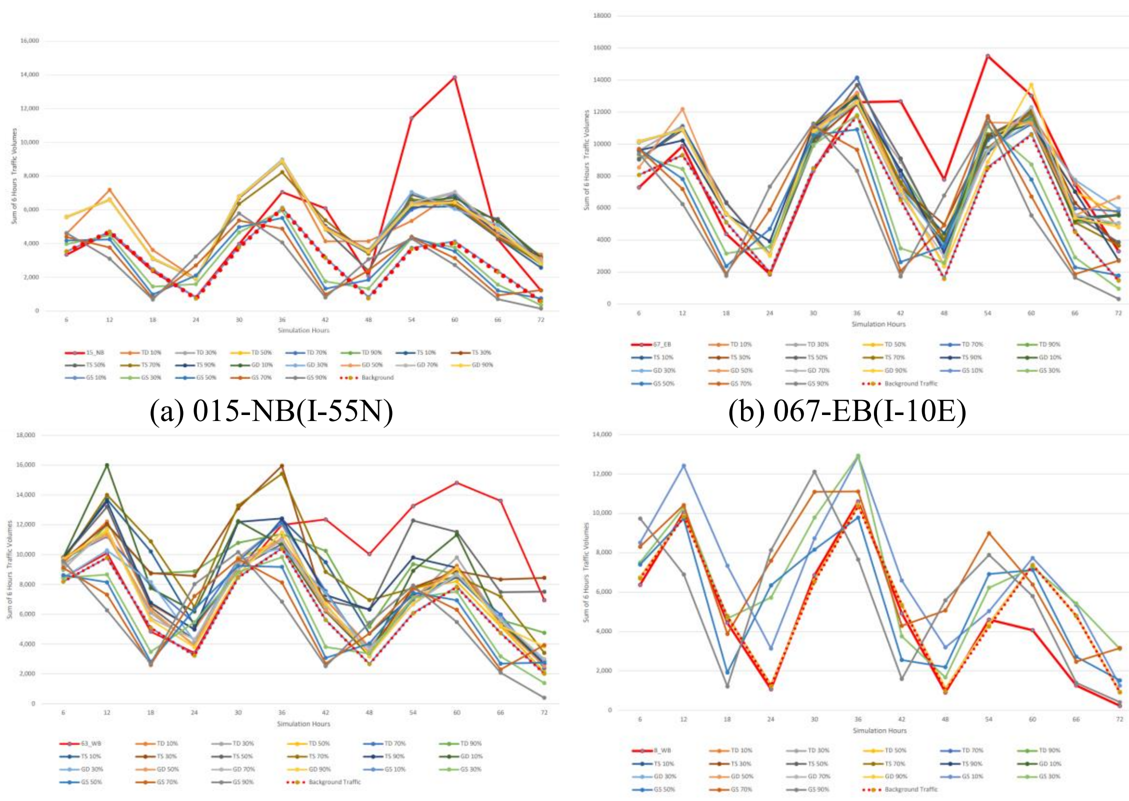
(c) 063-WB(I-10W)

(d) 008-WB(US-90W)

Figure 10 shows traffic volume summarized by 6 hour time intervals to assist in visual observations. While the traffic patterns are similar to one another in different scenarios, the variations among scenarios are not negligible. For example, traffic volumes are especially high on I-10W (063-WB) in the scenario of minimizing generalized cost in the deterministic shortest path model with only 10% informed drivers (i.e., GD10%). This indicates that I-10W would attract more evacuation traffic when only a small percentage of drivers are aware of the traffic situation and prefer taking the shortest path. Another example is that the simulated traffic patterns on US-90W seem not to change from scenario to scenario since many lines overlap with one another.

Figure 9 and Figure 10 both show that the current simulation underestimated traffic volume on I-55N and I-10W for the day before storm landfall. This may be because the study area covers only four parishes in the New Orleans metropolitan area, but people living outside of those four parishes, such as those living in Hammond, may also evacuate during the storm.

Figure 10. Comparison of traffic volumes summarized by 6 hour intervals



(a) 015-NB(I-55N)

(b) 067-EB(I-10E)

(c) 063-WB(I-10W)

(d) 008-WB(US-90W)

The following two tables present the results of evaluating which scenario provides the best fit using the mean squared error (MSE) as the evaluation criterion. A smaller MSE usually means a better match between the observed and simulated traffic volume. The MSE values from various scenarios were ranked for each location. A smaller rank number indicates that the simulated results are closer to the actual observations within 72 hours of the hurricane landfall.

As shown in Table 6, the lowest MSE appears in the TS30%, TS50%, or TS70% scenarios. This indicates that minimizing travel time in the stochastic shortest path model with a medium number of informed drivers would provide the best fit. In contrast, the highest MSE appears in the GS90%, GD90%, GD10%, or GS70% scenarios. This means that minimizing generalized cost with either the greatest or least amount of informed drivers would provide the worst fit.

It is also illuminating to consider each route choice scenario factor individually. When considering only the minimized item, travel time outperforms generalized cost (i.e., TD > GD, TS > GS). When considering only the shortest path model, the deterministic model outperforms the stochastic model (i.e., GD > GS, TD > TS). When considering only the percentage of informed drivers, 70% and 50% outperform the other values.

Table 6. Hourly traffic volume analysis

	Loc ID	015-NB		067-EB		063-WB		008-WB	
	Route	**I-55N**		**I-10E**		**I-10W**		**US-90W**	
	Inf Dr	**MSE**	**Rank**	**MSE**	**Rank**	**MSE**	**Rank**	**MSE**	**Rank**
TD	10%	351864	15	395135	5	628122	2	66104	4
	30%	292437	3	390594	3	677512	3	66228	15
	50%	302483	7	393413	4	724561	10	66113	7
	70%	296722	5	401873	6	751198	12	66110	6
	90%	296403	4	376055	2	690424	5	66106	5
TS	10%	321057	14	434421	12	736417	11	66102	3
	30%	314896	12	403352	7	773127	18	66062	1
	50%	316434	13	363054	1	466614	1	66160	12
	70%	282069	1	431492	11	705100	8	66145	9
	90%	306960	9	406977	9	789399	19	66139	8
GD	10%	301775	6	404728	8	791501	20	66093	2
	30%	314228	11	446406	13	694361	7	66180	14
	50%	305664	8	413470	10	716242	9	66156	11
	70%	291457	2	460034	16	679247	4	66169	13
	90%	310082	10	500144	20	691936	6	66150	10
GS	10%	415192	16	460005	15	761422	13	195029	18
	30%	416911	18	462047	18	761625	14	219624	19
	50%	415762	17	458883	14	762909	15	108567	16
	70%	418897	19	462631	19	763696	16	219941	20
	90%	420405	20	460632	17	764555	17	131456	17

Table 7 and Figure 10 are related, as they both present results by 6 hour intervals. Here the MSE values are greater than those presented in Table 6 because the time duration increases in each successive interval. As shown, the lowest MSE appears in the GD70%, TS50%, and TS10% scenarios. Although minimizing travel time in the stochastic shortest path model still provides the best fit in most cases, the percentage of informed drivers that provide the best fit changes. Additionally, minimizing generalized cost in the deterministic shortest path model with 70% of informed drivers performs well in one case. In contrast, the highest MSE consistently appears in the GS90% scenario. This indicates that minimizing generalized cost with the greatest number of informed drivers would provide the worst fit, which coincides with what was observed from Table 6.

The following observations can be made when considering one route choice scenario factor at a time. When considering only the minimized item, travel time outperforms generalized cost (i.e., TS > GS). When considering only the shortest path model, the deterministic model still outperforms the stochastic model (i.e., TD > TS). When considering only the percentage of informed drivers, 70% and 50% still outperform the other values.

Overall, both minimizing travel time and using the deterministic shortest path model generally produce lower MSE. This finding is somewhat unexpected. Further investigation is needed to determine whether the larger error from minimizing generalized cost item is due to factors influencing evacuation route choice behavior that have not yet been fully integrated into the simulation, such as accessibility and service facilities. Additionally, the deterministic shortest path should perform better in a smaller scale simulation in non-emergency situations where there is little or no variation in the available paths drivers may choose between any given OD pair. It may be helpful to test the current simulation with additional storm scenarios to draw a more generalized conclusion. Aside from the surprising findings described above, the percentage of informed drivers was found to be approximately 50-70%, which seems to be a realistic distribution.

Table 7. Traffic volume analysis by 6 hour intervals

	Loc ID	**015-NB**		**067-EB**		**063-WB**		**008-WB**	
	Route	**I-55**		**I-10E**		**I-10W**		**US-90**	
	Inf Dr	**MSE**	**Rank**	**MSE**	**Rank**	**MSE**	**Rank**	**MSE**	**Rank**
TD	10%	9809447	15	7744803	6	19042168	4	2057602	9
	30%	8420460	2	7383030	5	19352408	5	2059030	14
	50%	8923687	7	7296839	4	21664730	14	2057292	7
	70%	8829048	6	8433380	9	20333659	11	2056549	2
	90%	8757385	4	7007185	3	16972842	3	2059696	15
TS	10%	9479095	14	8645632	11	20039304	7	2054446	1
	30%	9299509	13	6683490	2	21634375	13	2056972	5
	50%	8939774	8	6055745	1	9126674	1	2057022	6
	70%	8579382	3	8354584	8	20104873	8	2057619	10
	90%	9025125	10	8027006	7	16877208	2	2057572	8
GD	10%	8797058	5	8462773	10	22287037	15	2056934	4
	30%	9123278	11	9015012	12	20283787	10	2058728	12
	50%	9023832	9	9246823	13	20515125	12	2056829	3
	70%	8332915	1	9782815	14	20110383	9	2058882	13
	90%	9140031	12	10766355	15	19834206	6	2058622	11
GS	10%	14039609	16	11962653	16	25386172	16	5911026	17
	30%	15270646	17	15768984	17	30093321	17	6441848	18
	50%	16316400	18	18298578	18	31600428	18	5286708	16
	70%	18035163	19	21519605	19	33785708	19	9767559	19

	Loc ID	015-NB		067-EB		063-WB		008-WB	
	Route	I-55		I-10E		I-10W		US-90	
	Inf Dr	MSE	Rank	MSE	Rank	MSE	Rank	MSE	Rank
	90%	20190322	20	26530704	20	39997866	20	13701722	20

Conclusions

This project simulated the hurricane evacuation behavior choices of households with models developed in the past and simulated evacuation traffic patterns in the last 72 hours prior to the landfall of Hurricane Ida. In this process, the challenges of collecting data to generate synthetic populations, the shift of local demographics over the last decade, lessons learned in model transferability, and updates to the traffic simulation with drivers' route choice behavioral parameters integrated were discussed to facilitate upgrading traditional evacuation simulations to digital twin creation for future storm responses. This process also emphasizes that human components, including demographic profiles and behavior choices, should not be overlooked in the process of creating digital twins for disaster responses. The following is a summary of major findings, including implications for practice and future studies.

Synthetic Populations

The best current data sources to generate synthetic populations in the U.S. are the Public Use Microdata Sample (PUMS) and the American Community Survey (ACS). However, simulating a hurricane before 2013 has become challenging due to the availability of various datasets for all of the factors needed to generate these populations. This highlights the importance of data sharing and management. However, sharing data for all of the years for public inquiry may be challenging due to database maintenance limitations.

Local Demographics

The total population, average household size, average household vehicle ownership, and census zone boundaries have all changed in the study region in the last decade. These are essential factors that influence evacuation traffic generation, which necessitates that researchers be careful in using proper datasets in their simulations. Additionally, many ongoing issues, including the changing of local landscapes due to natural disasters and paradigm shifts such as managed retreat, can influence local demographics long term and thus affect local disaster management plans.

Model Application and Transferability

Storm location by time affects parameter setup for the lognormal distance function used in the evacuate/stay and departure timing joint choice models. Additionally, destination risk perceptions significantly influence household destination choices, which are potentially associated with real-time storm track forecasts rather than the best storm track. Values for both factors could be updated in real time with live storm feeds. Note that the updates are related to factor value updates (i.e., external conditions) rather than behavioral model parameter updates (i.e., internal choice mechanisms). In this study, the prediction error can be controlled within 5% without updating behavioral model parameters. This means that evacuation choice mechanisms can remain the same from storm to storm.

Integrating Drivers' Route Choice Parameters into Traffic Simulation

In this study, the best set of route choice parameters is minimizing travel time in the stochastic shortest path model with a medium number of informed drivers. Further studies should be performed in other storm scenarios to determine if and how this set of parameters may vary. It should be noted that several perspectives, including simulation road network corrections (e.g. lane connectors and roadway/intersection geometry) and traffic signal timing plan improvements, should be utilized in updating a traditional traffic simulation framework to achieve a better virtual environment for evacuation traffic simulation and subsequent digital twin creation.

The findings outlined above are expected to be helpful in making models previously estimated for a local region useful for predicting the hurricane evacuation-related choices of households in new storm scenarios. Such applications and improvements will make use of existing resources and reduce efforts for data collection. However, the current study also has limitations that necessitate further research, such as developing statistical models to better set up parameters in the lognormal distance function and measuring household destination risk perceptions using social media feeds. Additionally, census data are typically released with an unavoidable time lag in practice. For example, the 2018-2022 American Community Survey (ACS) 5-Year Estimates were released in December 2023. As the Atlantic hurricane season begins in June 2024, the census data available for population synthesis are backdated to reflect local demographics in 2022. For future research, a reliable synthetic population dataset for a current year needs to be generated to create a successful digital twin that reflects real world conditions.

There are also several limitations that require further research in simulating evacuation traffic. Currently, only one item (i.e., interstate highways) is considered in the generalized cost function. Additional items should be considered, and their coefficients can be tested and estimated via traffic simulation. Comparisons could then be made against evacuation route choice models estimated with household survey data. Additionally, this study used traffic observations from the week before Hurricane Ida made landfall as the background traffic. Future research could use real-time traffic flow data or human mobility data collected via mobile devices to adjust the percentage of background traffic loading for different routes to create a better performing digital twin.

Recommendations

In its current version, the HEMP can provide statistics, such as the number of evacuees and average evacuation traffic speed/time in 6 hour intervals from 72 hours prior to storm landfall, to evaluate when and where to issue an evacuation order and determine when and where bottlenecks exist to support traffic operations for congestion mitigation.

From an academic perspective, advances in communication technologies make collecting and transmitting near-real-time data possible, which makes the concept of digital twins possible in transportation applications. An important difference between a digital twin and traditional evacuation simulation is the ability to absorb real-time information, which is expected to create a virtual environment that more closely corresponds to real world conditions [68]. Upgrading existing evacuation simulations to create digital twins could be a cost-effective approach to better understand what real-time input is needed. This approach could also work in regions that have a limited number of sensors that can provide data to support machine/deep learning models as the sole input for digital twin creation. The efforts made in creating such digital twins will better support disaster management with accessible, understandable, and useful outputs from computational models. Such a process would require collaborative partnership between academic and public agencies.

From an implementation standpoint, computer-generated simulation results should be evaluated, trained, and improved by utilizing the human knowledge, experience, and instincts accumulated throughout years of practice after disasters. Creating academic-public partnerships for tool improvement, testing, and use would require additional resources, such as purchasing computing resources and developing training activities. Within the current project capacity, the following implementation-related activities could be pursued in the near term:

- Involve the research team in disaster response exercises, allowing them to run the tool and gain a better understanding of its use in practice.
- Include research team members in disaster response trainings, allowing them to interact with emergency managers and operators to better understand their needs.
- Create internship opportunities for students to grow the future workforce in this field.

Acronyms, Abbreviations, and Symbols

Term	Description
AASHTO	American Association of State Highway and Transportation Officials
ACS	American Community Survey
ArcGIS	Geographic Information System software by ESRI
AReBIC	A reservation-based intersection control algorithm
CAV	Connected and Autonomous Vehicle
cm	centimeter(s)
COVID-19	Coronavirus Disease 2019
DYNEV	Dynamic Network Evacuation
EB	eastbound
ETIS	Evacuation Traffic Information System
FHWA	Federal Highway Administration
FL	Florida
ft.	foot (feet)
GD	Minimize Generalized Cost, Deterministic Shortest Path Model
GD90%	Minimize Generalized Cost, Deterministic Shortest Path Model, and 90% Informed Drivers
GISDK	Geographic Information System Developer's Kit
GS	Minimize Generalized Cost, Stochastic Shortest Path Model
GPU	Graphics Processing Unit
HEMP	Hurricane Evacuation Modeling Package
HES	Hurricane Evacuation Studies
HINCP	Household Income
HURREVAC	Hurricane Evacuation System
in.	inch(es)
InfDr	Informed Drivers Percentage
IPU	Iterative Proportional Updating
ISE	Integrated Scenario Ensemble-based Evacuation
LADOTD	Louisiana Department of Transportation and Development
lb.	pound(s)
LTRC	Louisiana Transportation Research Center
m	meter(s)
MSE	Mean Squared Error
NB	northbound

Term	Description
NHC	National Hurricane Center
NOLA	New Orleans
NP	Number of persons associated with a household record
OD	Origin-Destination
OREMS	Oak Ridge Evacuation Modeling System
PTV Vissim	A microscopic simulation program for multi-modal traffic flow modeling
PUMA	Public Use Microdata Area
RAM	Random Access Memory
SB	southbound
Std Dev	Standard Deviation
SUMO	Simulation of Urban Mobility
TS	Minimize Travel Time, Stochastic Shortest Path Model
TD	Minimize Travel Time, Deterministic Shortest Path Model
TransCAD	A software for transportation planning by Caliper
TRANSIMS	Transportation Analysis and SIMulation Systems
TransModeler	A based traffic simulation platform for doing wide-area traffic planning, traffic management, and emergency evacuation studies
UE	User Equilibrium
VEH	Number of Vehicles available to a household record
VLADIMIR	Variable Legend Assessment Device for Interactive Measurement of Individual Route Choice
WB	westbound
ZCTA	Zip Code Tabulation Area

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