Network Wide Evacuation Traffic Prediction in a Rapidly Intensifying Hurricane from Traffic Detectors and Facebook Movement Data: A Deep Learning Approach

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ABSTRACT:

Traffic prediction during hurricane evacuation is essential for optimizing the use of transportation infrastructures. It can reduce evacuation time by providing information on future congestion in advance. However, evacuation traffic prediction can be challenging as evacuation traffic patterns is significantly different than regular period traffic. A data-driven traffic prediction model is developed in this study by utilizing traffic detector and Facebook movement data during Hurricane Ian, a rapidly intensifying hurricane. We select 766 traffic detectors from Florida's 4 major interstates to collect traffic features. Additionally, we use Facebook movement data collected during Hurricane Ian's evacuation period. The deep-learning model is first trained on regular period (May-August 2022) data to understand regular traffic patterns and then Hurricane Ian's evacuation period data is used as test data. The model achieves 95% accuracy (RMSE = 356) during regular period, but it underperforms with 55% accuracy (RMSE =

1084) during the evacuation period. Then, a transfer learning approach is adopted where a pretrained model is used with additional evacuation related features to predict evacuation period traffic. After transfer learning, the model achieves 89% accuracy (RMSE = 514). Adding Facebook movement data further reduces model's RMSE value to 393 and increases accuracy to 93%. The proposed model is capable to forecast traffic up to 6-hours in advance. Evacuation traffic management officials can use the developed traffic prediction model to anticipate future traffic congestion in advance and take proactive measures to reduce delays during evacuation.

PRACTICAL APPLICATIONS:

Hurricane evacuation causes significant traffic congestion in transportation networks. Increased traffic demand can affect evacuation process as it delays the movement of people to safer locations. To remedy this issue, an accurate traffic prediction model is beneficial for evacuation traffic management. The prediction model can give expected traffic volume on evacuation routes well in advance which will allow traffic management agencies to prepare for and activate strategies such as emergency shoulder utilization, adjustments to signal timing for optimal traffic flow etc. on those evacuation routes. This work aims to construct a data-driven model for the purpose of predicting traffic flow with a lead time of up to 6 hours. The model can be used to make network-wide traffic forecasting in real time. Thus, practitioners can use this tool to effectively implement evacuation traffic management strategies by determining the timing, locations, and extent of those strategies based on predicted traffic volume. Another benefit of this model is that it can be trained with data from normal period and historical hurricane evacuations and then be implemented for future hurricanes.

AUTHOR KEYWORDS: Traffic Prediction, Graph Neural Network, Facebook Movement Data, Transfer Learning, Hurricane Evacuation, Hurricane Ian.

INTRODUCTION:

In recent years, coastal residents of the United States have experienced significant adverse effects from the occurrence of major hurricanes, including but not limited to Hurricanes Irma, Ida, Ian, Harvey, and Idalia. Hurricane events are getting alarmingly intense and frequent along US east coast, mostly due to global climate change (Knutson et al., 2022). Consequently, residents of the United States living near the coast are more likely to be hit by hurricanes, especially during rapidly intensifying hurricanes when people have less time to respond. Major hurricanes can be devastating and cause severe property damage and loss of lives (*Cost of Natural Disasters*, 2017). To mitigate such effects and save lives, emergency managers employ evacuation orders based on the time and location of the hurricane landfall. Although hurricane evacuation plays a vital role to save vulnerable population, evacuation traffic creates sudden demand surge causing traffic congestion and other issues such as increase in crashes and delays in reaching shelters. For example, about 6.5 million Floridians were ordered to leave their homes during Hurricane Irma (Viswanathan, 2021). This caused major congestions and major accidents on I-75 and I-95 (Rahman, Bhowmik, et al., 2021; Rahman, Hasan, et al., 2021). Several traffic management techniques are used to reduce heavy traffic, such as using the shoulder, allocating contraflow, giving clear instructions for evacuation routes, and so on. (Murray-Tuite & Wolshon, 2013). However, to efficiently manage evacuation, traffic managers need to understand the prevailing and future traffic condition of the network. A network-level traffic prediction model can assist emergency management for a proactive application of such strategies to efficiently manage evacuation traffic.

However, prediction of evacuation traffic is more difficult due to uncertain demand variations from regular period traffic. Evacuation traffic pattern does not show any peaking (morning and evening peak) behavior like regular traffic. Moreover, during evacuation period the road network remains congested for a prolonged period of time resulting in stop and go traffic conditions. Additionally, a sudden change of hurricane path can cause changes in evacuation orders. As a result, it induces sudden demand surge on different evacuation routes. Traditionally, mathematical modeling and simulation methods have been used to forecast evacuation traffic (Barrett et al., 2000; Chen et al., 2020; Q. Li et al., 2006). These approaches rely on user-equilibrium solutions based on mathematical assumptions to estimate network wide traffic, which might not hold true during an evacuation period. Moreover, lack of input from real-time traffic data makes these approaches less robust against sudden demand surge. To address this issue, data-driven methodologies can be used. Data-driven models can forecast future traffic by analyzing historical evacuation traffic patterns and traffic data. These models do not rely on any assumptions about the behavior of evacuees.

Traditionally data-driven models of traffic prediction are formulated as simple time series problems. In such approaches, various models such as ARIMA, SARIMA, SARIMAX, K Nearest Neighbor (KNN), Support Vector Regression (SVR), Decision Tree, Artificial Neural Network (ANN) models have been widely used (Ahn et al., 2016; Brian Smith & Demetsky, 1997; Cai et al., 2016). However, spatiotemporal time-series prediction problems are more complicated since they require capturing both spatial and temporal correlation among traffic variables (Jiang & Luo, 2022). Such traffic prediction problems require models which can deal with higher dimensionality of traffic variables. Hence, traditional modeling approaches are not suitable for spatiotemporal traffic prediction. Recent developments in machine learning have pushed the boundary of traditional ANN models and enabled learning of high dimensional data through multilayered parameters known as deep learning. Deep learning techniques such as Convolutional Neural Networks (CNNs) and Graph Convolutional Neural Networks (GCNNs) can learn spatiotemporal variations in traffic patterns to forecast future traffic; providing more accurate predictions compared to traditional models (Ahn et al., 2016; Cai et al., 2016; Innamaa, 2005).

This study employs the Graph Convolutional Neural Network (GCNN) architecture to forecast network-wide traffic volume during evacuations. GCNN models acquire knowledge of the transportation network by conceptualizing it as a graph, in which road intersections are represented as nodes and roads that connect those intersections are regarded as edges. These models are structured to learn traffic state such as intersection level traffic volume, link travel time or speed of an entire network via a graph convolution layer. The graph convolution layer utilizes a graph theoretic approach to extract spatial cross correlations among input features (Wu et al., 2021). Many studies have applied different graph representation techniques to achieve cutting edge traffic prediction accuracy (Wu et al., 2019). However, one of the limitations to train such large-scale models is that they need extensive data. Hence, most of the previous studies applied GCNN models for regular traffic conditions where they have enough data to train the model. On the contrary, in our approach we create the model to forecast traffic throughout the evacuation period of a rapidly intensifying hurricane. Since the evacuation period in such events lasts for only 1 to 3 days, available data is not sufficient to train such large-scale models. To overcome this issue, in this study we adopt a transfer learning approach similar to what was proposed in (Rahman & Hasan, 2023).

We utilize a Dynamic Graph Convolution Neural Network (DGCNN) based deep learning architecture to forecast network-wide evacuation traffic for Hurricane Ian's evacuation period. We call our model 'dynamic' because it utilizes variations of travel time at each time step to understand the congestion propagation at the whole network. On September 28, 2022, Hurricane Ian made landfall in Florida. It was a rapidly intensifying hurricane, and the evacuation orders were placed just two days (September 26-27, 2022) before the hurricane. So, we have data of only two days from the hurricane evacuation period to train the model. Due to data scarcity of evacuation period, we train our model with regular period data (May 15– August 15, 2022) and test the model performance for evacuation period traffic.

For training the model, we use data from two sources. Like previous studies, we use traffic data from roadway detectors. The Florida Department of Transportation (FDOT) maintains Microwave radar

Vehicle Detection System (MVDS) detectors on the interstate roads in Florida. These detectors provide traffic data such as speed, volume, occupancy at high spatiotemporal resolutions (Ghorbanzadeh et al., 2021; Rahman, Roy, et al., 2021). Moreover, to improve the accuracy of the model and capture the variations in evacuation traffic demand, we also use social media data as an input to the model. We use mobility data from 'Data for Good at Meta' platform which provides movement between places during crisis events such as hurricanes (*Data for Good at Meta*, 2022). The data consists of aggregated real-time movements of Facebook users between different administrative levels at 8-hour intervals. We develop a data processing tool to integrate this mobility data with traffic detector data for the entire interstate network of Florida.

We develop the prediction model focusing on the hypotheses that there is a strong correlation between the number of evacuees (from social media data) and change in surge of traffic demand (from traffic detector data) in major freeways during evacuation period. The main contributions of this study are as follows:

i. It extends the deep learning-based traffic prediction model developed by Rahman & Hasan (2023) by incorporating Facebook movement data to better capture the spatiotemporal dynamics of evacuation demand even for a rapidly intensifying hurricane;

ii. It identifies the challenges and develops methods to process discontinuous Facebook movement data to reveal real-time evacuation travel demand variations; and

iii. It demonstrates the utility of Facebook movement data to improve the accuracy of spatiotemporal traffic prediction model; to the best of our knowledge Facebook movement data was never considered in traffic prediction models.

LITERATURE REVIEW:

Evacuation studies used statistical patterns to analyze individual evacuation behaviors (Dow & Cutter, 1998; DRABEK, 1992). Later, different discrete choice models were used to determine contributing factors to people's evacuation decisions (Lindell et al., 2018; Murray-Tuite & Wolshon, 2013; Wong et al., 2018). Researchers previously focused on analyzing factors that lead to evacuation decisions (Fry & Binner, 2016; Hasan et al., 2011, 2013), mobilization time (Sadri et al., 2013), departure time (Pel et al., 2012), destination choice (Mesa-Arango et al., 2013; Wilmot, 2006), evacuation mode and destination type (Bian et al., 2019), evacuation plan adaptation (Bian et al., 2022) etc. Insights from evacuation behavior studies can also benefit evacuation traffic modeling studies. For example, behavioral studies can provide information about potential evacuation routes, departure time or evacuation destinations. Previously, several studies used mathematical or simulation-based frameworks to model evacuation traffic demand. For example, Chen et al. (2020) developed a simulation-based framework to predict evacuation traffic due to wildfire. Other studies used different optimization techniques to increase evacuation efficiency (Shahabi & Wilson, 2018).

There are several limitations of evacuation behavior studies. They mainly utilized survey data which are expensive and may not represent the overall population. Also, survey-based studies do not perform well in traffic prediction models due to low sample size. Additionally, simulation-based studies use several assumptions on population behavior which may not capture well actual evacuation traffic demand.

Social media data can be used to overcome limitations of traditional approaches for prediction of evacuation traffic. They provide geotagged posts which can provide population density during evacuations. We can also get information about traffic congestions which can be integrated to transportation network for better traffic prediction. Previous studies used social media data to detect natural disasters (Kryvasheyeu et al., 2015) and modeling human mobility (Roy et al., 2019). Another study extracted evacuation behavior from Twitter for traffic prediction at the level of a road segment (Roy et al., 2021). Although previous studies used Twitter to analyze evacuation behavior, Twitter data has several limitations such as it lacks representativeness and cannot provide any meaningful variable that can be readily used for any traffic prediction models (Carley et al., 2016). Additionally, researchers used various filtering algorithms to extract information from raw Twitter data, potentially introducing biases in model results (Wang & Ye, 2018).

Alternatively, population data provided by Facebook's 'Data for Good at Meta' platform can be used to analyze population distribution during evacuation. This data provides several useful metrics such as 'z-score' that can be used to identify hot spots of population distribution during crisis events (Jia et al., 2020). Facebook also provides movement data which illustrates anonymous people movement between administrative regions during crisis events. The movement data collects movements for those users who turn on their device's GPS location at 8-hour intervals. This data provides highly granular information of evacuation dynamics which Twitter data cannot provide. Also, movement data provides important insights which can be beneficial for modeling evacuation demand. This data has not been previously used to predict evacuation traffic.

Recent developments of high computational power have enabled researchers to use different deep learning models such as Long Short-Term Memory (LSTM) model, Convolutional Neural Network (CNN), Graph Convolutional Neural Network (GCNN), or a hybrid approach of integrating those models such as CNN-LSTM or GCNN-LSTM models etc. to predict traffic state with higher accuracy (Cui et al., 2020; Y. Li et al., 2018; Zhao et al., 2020). Jiang & Luo (2022) concluded that Graph Neural Network (GNN) based models are becoming popular in traffic prediction studies. Majority of these GNN models were developed to predict traffic in regular conditions. They cannot be used for evacuation traffic prediction because there is a significant difference between regular traffic and evacuation traffic (Rahman, Hasan, et al., 2021). Recently, Rahman & Hasan (2023) proposed a DGCN-LSTM model to predict evacuation traffic during Hurricane Irma considering traffic detector data. However, they didn't use any social media data as an input feature that would represent evacuation demand.

In summary, existing deep learning-based traffic prediction models considered only traffic detector data to predict regular period traffic states. Few studies considered network-level evacuation traffic dynamics by using traffic detector data. In this study, we propose a methodology that combines both detector data and Facebook movement data to predict evacuation traffic for a rapidly intensifying hurricane. The methodology can be applied to all emergency events where evacuation period lasts for a short period of time.

DATA DESCRIPTION

Traffic Detector Data

In this study, we collected hourly traffic detector data from Regional Integrated Transportation Information System (RITIS) which provides real-time information on traffic speed, volume, occupancy at a high resolution (*RITIS*, 2022). We selected four major interstates of Florida: I-95 (northbound), I-75 (northbound), I-4 (eastbound) and Florida's turnpike (northbound) based on analyzing the major evacuation routes from previous hurricanes in Florida (Rahman, Roy, et al., 2021). We collected regular period traffic detector data from May 15 – August 15, 2022, and evacuation period traffic detector data of Hurricane Ian from September 26 – September 27, 2022. We processed the raw data to discard detectors with missing data, zero values etc. The details of data processing are discussed in the Methodology section. After data processing was done, we selected 766 detectors to construct the graph network. **Fig. 1** shows the location of detectors after data processing.

Facebook Movement Data

We also extracted Facebook movement data from “Data for Good at Meta” platform that provides the number of people moving between administrative regions at 8-hour intervals during Hurricane Ian’s evacuation period. The data includes Facebook users’ mobility information for **two separate 8-hour periods** 3 am-11 am and 11 am-7 pm during Hurricane Ian’s evacuation period. Facebook did not provide any movement data for 7 pm-3 am in each day. The dataset also included baseline movement data between tiles, the baseline period data was collected 45 days before the movement map was first generated (*Data for Good at Meta*, 2022). The extracted data include users’ movements between small geospatial tiles of Bing tile level 14, where each tile is a square having length of 2.4 kilometers on each side. The approximate area of a tile is around 5.76 square kilometers (Maas et al., 2019). We assumed that most people who evacuated using freeways must travel longer distance than what was provided in tile-level movement data. So, we aggregated tile-level movements to county subdivision level movements. Details about the movement data processing are described in the Methodology section.

Hurricane Ian made landfall on the west coast of Florida with 12 counties on the western coast issued mandatory evacuation orders on September 27, 2022 (Ian Evacuation, 2022). **Fig. 2** shows evacuation zones under mandatory evacuation orders along with respective zone level during Hurricane Ian. Zone level A denotes a high-risk zone while zone level E indicates a low-risk zone. Majority of these evacuation zones were in the west coast as Hurricane Ian was predicted to hit Florida from the west coast.

We compared percent increase of movement patterns in the evacuation period compared to the baseline period. The baseline period is 45 days before the movement data is first generated. Charlotte, Pinellas, Pasco, Hillsborough, Levy, Manatee, and Sarasota counties issued mandatory evacuation orders on September 26 (Anand et al., 2024). All of these counties are situated in the west and southwest coast of Florida. We observe a significant increase of users’ movements on September

26. Majority of these movements generated from Central Florida, west and southwest coasts of Florida. **Fig. 3** shows the movement patterns starting at 3 am and ending at 11 am of September 26 (2 days before landfall time). The percentage of movement increased in west coast of Florida as residents were informed about the hurricane and evacuation orders were being issued. Some people also evacuated between western regions, so the number of movements that were destined to west coast also increased on September 26. This is expected as people tend to move towards more inland location so that storm surge or flood risk can be mitigated. We also compared the number of movements originated in different counties situated in the west and southwest coast of Florida and the number of movements ended in counties of central Florida region as shown in **Fig. 4.** By utilizing Facebook movement data, we can infer certain evacuation movement patterns. On September 26, people moved from west and southwest coast which include cities such as Tampa, St. Petersburg to Central Florida region. From the Facebook movement data, we observe increased movements in Central Florida, southeast, and west coast regions compared to the baseline movements.

Fig. 5 shows movement patterns during September 27 (3 am-11 am). Evacuation orders were already placed for 12 counties by this time period. We also compared the number of movements originated from counties situated in west and southwest coast and the number of movements ended in counties in Central Florida region as shown in **Fig. 6.** We observe that the number of movements decreased in the west coast compared to previous day's movements. It indicates that population in west coast also decreased on September 27 as people started evacuating from the region. We also found that higher numbers of movements ended in Central Florida region compared to the baseline period.

Based on our analysis from Facebook movement data, we found that majority of people evacuated from the western region to the Central Florida region. In regular traffic condition, Interstate I-4 Eastbound serves majority of traffic traveling from west coast to Central Florida region. To correlate the movement data with traffic volume data, we plot cumulative traffic volume for an eastbound detector of Interstate I-4; the detector is placed close to Central Florida (**Fig. 7**). We used cumulative hourly traffic flow instead of hourly traffic flow to compare whether I-4 Eastbound dealt with higher amount of traffic flow during the evacuation period. We chose 8-hour timeframe to match with the 8-hour timeframe of Facebook movement data as shown in **Fig. 4** and **Fig. 6**. We calculated mean traffic flow based on hour and day of the week from regular period traffic data (May 15 – August 15, 2022). Then we extracted cumulative baseline period flow of the selected detector. We found that during September 26, 2022, cumulative flow was around 25,000 vehicles and it reached around 50,000 vehicles on September 27, 2022. Facebook movement data shows increased movements in Central Florida during evacuation period, and traffic detector data also illustrates higher crisis period flow over baseline period flow. Additionally, many people evacuated from west coast to Central Florida through Interstate I-4 Eastbound, which explains increase in cumulative flow compared to baseline period cumulative flow. The human movement patterns from Facebook followed similar trends of the actual traffic movement during Hurricane Ian.

METHODOLOGY

Detector Data Processing

Raw traffic detector data is prone to errors due to detector malfunctioning, bad weather, duplicate or missing entries, wrong storing, etc. During hurricane evacuation period, majority of vehicle face ‘stop and go’ traffic congestion in major freeways, which detectors may fail to capture (Rahman & Hasan, 2023). To address these issues, we performed extensive data cleaning to prepare final training data for the deep-learning model. First, we removed detectors having missing values higher than 20% of the observations and zero values higher than 40% of the observations. Second, we discarded those detectors having traffic flow per hour per lane (vphpl) higher than 2500 (Rahman & Hasan, 2023).

Finally, we applied multivariate iterative imputation to fill up missing values (Pedregosa et al., 2011). **Fig. 8** provides the data-processing steps of traffic detector data.

Facebook Movement Data Processing

We followed several steps to process the Facebook users' movement data. Although the movement data were provided at a small geospatial tile level, we assumed that people evacuated further than a tile distance. So, we aggregated the movement volume in each tile's corresponding county subdivision level. There were two types of movement: evacuation within a county subdivision (origin and destination of the movement falls within the same county subdivision) and evacuation between county subdivisions (origin and destination are different county subdivisions). We discarded movements occurring within the same subdivision considering that these movements might not use highways. Then, we assigned closest traffic detectors from RITIS for each movement's origin and destination county subdivisions. We assigned the closest detector based on the minimum distance between the centroid of a county subdivision and selected 766 detectors from RITIS. Then we checked whether the origin and destination traffic detectors of a movement match; if so, we assumed that this movement was less likely to use any highways to evacuate; this was mainly reflecting the movement inside a county subdivision. For each detector, we aggregated the number of inflow and outflow values of Facebook users.

The processed movement data contains aggregate inflow and outflow in 8-hour intervals. We disaggregated them to 1-hour movement by applying an hourly factor calculated from the traffic flow data. We disaggregated the movement data to match with traffic detector data which was processed at 1-hour intervals. **Eq. 1** shows the formula for estimating the hourly factor.

$$hourly\ factor\ for\ hour\ z = \frac{F_z}{\sum_{z=1}^{8} F_z} \qquad (1)$$

Where F_z indicates total traffic flow of all 766 detectors in 1-hour interval and z denotes the hour ranging from start to end of the 8-hour interval. We used data from the whole network in the denominator of **Eq. 1** to avoid adding any localized bias to the movement data. If we use smaller subsection of the network and calculate total traffic flows of the subnetwork in calculating the hourly factor, the Facebook movement data will be highly correlated to the traffic detector data. As a result, the hourly human mobility patterns will follow closely to traffic detector data, and it will create localized bias to the movement data. To avoid this issue, we used whole network's traffic detector data. Then, we multiplied the 8-hour Facebook movement data with the hourly factor to disaggregate it to hourly movement data as shown in **(Eq. 2)**. **Fig. 9** shows the workflow used to process the Facebook movement data.

$$hourly\ movement\ data = Facebook\ movement\ data \times\ hourly\ factor \qquad (2)$$

Problem Formulation

In this study, we predict network-level evacuation traffic flow given that traffic volume and evacuation demand data are available at a higher spatiotemporal resolution. To solve this problem, we adopted similar approach of Dynamic Graph Convolution Neural Network and Long Short Term Memory **(DGCN-LSTM)** model developed in (Rahman & Hasan, 2023). We used two stacked layers in our deep learning model. In the first layer, we used dynamic graph convolution (DGCN) operation to capture the spatial cross correlation among traffic state related features. In the dynamic graph convolution approach, weights of the graph were assigned based on changes in travel time between two detectors at each timestep. In the second layer, we used a LSTM unit to capture the temporal dependency among the input features.

Let, X_t be the input features coming from both traffic detector and Facebook movement data. We considered the transportation network as a graph and each traffic detector as a node. The graph is represented as $\mathcal{G}_t(v, e, A_t)$ where v is the set of all nodes (detectors), e denotes the set of edges between detectors (road segment between two detectors) and A_t denotes the weighted adjacency matrix. In our prediction problem, we learn a function $\mathcal{F}$ that takes l instances of input sequences $([X_{t-l}, X_{t-l+1}, \ldots.., X_t])$ and predicts future traffic flow $(F_{t+1}, \ldots\ldots, F_{t+p})$ for p instances. We can define the problem via **Eq. 3.**

$$\mathcal{F}([X_{t-l}, X_{t-l+1}, \ldots.., X_t]; [\mathcal{G}_{t-l}(v, e, A_{t-l})]) = [F_{t+1}, \ldots\ldots, F_{t+p}] \qquad (3)$$

We used weighted adjacency matrix instead of regular adjacency matrix to make the graph dynamic. The weighted adjacency matrix contains information of change in travel time between detector pairs for each time step. The travel time depends on the speeds of two consecutive detectors at each timestep. Since the weighted adjacency matrix is dynamic and function of travel time, the prediction model can learn the network-level congestion propagation with respect to changes in travel time. The equation of weighted adjacency matrix A_t is defined by **Eq. 4.**

$$A_t(i,j) = \begin{cases} tt_t(i,j), & if\ i \neq j \\ 0 & if\ i = j \end{cases} \qquad (4)$$

Equation of travel time, $tt_t(i,j)$ depends on distance $(d^{i,j})$ and speed of two consecutive detectors (s_t^i, s_t^j) at each time step as shown in **Eq. 5**.

$$tt_t(i,j) = \frac{d^{i,j}}{\frac{s_t^i + s_t^j}{2}} \qquad (5)$$

The proposed framework of the **DGCN-LSTM** model is illustrated in **Fig. 10.** The model takes l = 6 hours of sequential data as input and predicts traffic volume for next p = 6 hours.

Transfer Learning Approach

To train the proposed DGCN-LSTM model, a substantial amount of input data is required. During regular period traffic prediction task, RITIS can provide high amount of traffic flow data. As a result, the proposed model can predict regular period traffic efficiently. But the goal of this study is to predict traffic flow during evacuation period. As the evacuation process lasts for a short period of time (2 to 5 days) during a rapidly intensifying hurricane, the DGCN-LSTM model cannot be trained with sufficient data. To overcome this issue, we adopted a transfer learning approach (Zhuang et al., 2021).

We first trained the DGCN-LSTM model with regular period data. Then we applied transfer learning approach to predict for evacuation period. However, there is a significant difference between regular and evacuation period traffic. The traffic demand can increase significantly due to evacuation process. Additionally, evacuation period doesn't show any regularity in traffic patterns. To overcome this issue, we extracted only necessary information such as transportation network connectivity and how traffic flow propagates along the network through all detectors by using transfer learning.

The transfer learning approach is divided into 4 parts. The first part is the pretrained DGCN-LSTM model with regular data. We used this model to predict evacuation period traffic. Then, the second part consists of a LSTM model where we trained the LSTM model with evacuation traffic state features along with evacuation demand related features such as distance between a detector and nearest evacuation zone, time left before hurricane landfall, and cumulative population placed under mandatory evacuation orders. The third part is called control layer which is a neural network block with sigmoid activation function. The control layer controls necessary information coming from the output of the DGCN-LSTM model via sigmoid activation function. The fourth layer is called output layer which adds output of second and third layer together to provide final output of evacuation period traffic. Details about the transfer learning approach are described in (Rahman & Hasan, 2023). **Fig. 11** illustrates the transfer learning approach to predict evacuation period traffic. Orange boxes indicate four parts of the transfer learning model, blue boxes indicate input features, and the green box indicates final output of evacuation traffic flow.

Methodology to Handle Discontinuous Facebook Movement Data

Facebook provided daily movement data for 16 hours instead of 24 hours due to technical issues. Although we had traffic detector data for 24 hours, we didn't use detector data from 7 pm to 3 am of next day. We selected RITIS detector dataset for following time periods: September 26 (3 am – 7 pm) and September 27 (3 am – 7 pm) to match them with available Facebook movement data. As a result, our sample size for each day reduced to 16 hours. To handle such discontinuity in the dataset, we adopted an indexing approach where we gave an index number for each sequential 6-hour observations in our dataset. Each index represents a 6-hour time series observation. For example, an index represents traffic state observations for 5 am, 6 am, 7 am, 8 am, 9 am, and 10 am as input features of the DGCN-LSTM model. The next index contains time series observations of 6 hours from 6 am to 11 am. For each index, we maintained the temporal sequence (6-hour time series), which means that the model takes inputs of 6 hours of time series data to forecast the next 6 hours of traffic flows. We did not change the order of the time series (6 hour) in each index when feeding input data to the model. Then, we run the prediction model for 10 times. In each iteration, different set of index numbers were randomly selected for training, validation, and testing dataset observations. As a result, in each iteration, we have different data for training, validation, and testing purposes. Because of the random selection, the index numbers did not have to be consecutive. As a result, the missing 8-hour timeframe of each day did not affect the model's learning process of how traffic flow propagates in the whole network. By adopting this randomly selected index numbers, the model becomes more robust against the discontinuity in Facebook movement data.

INPUT FEATURES

We used features shown in **Table 1** as input to the prediction model. We used several non-evacuation related features to train the prediction model for regular period. We divided 16-hour time period into 4 different periods: **Early Morning** (3 am-7 am), **Morning** (7 am-11 am), **Mid-day** (11 am-3 pm), **Evening** (3 pm-7 pm). Additionally, we used previous day's mean and standard deviation of traffic flow, previous period's mean and standard deviation of traffic flow, weekday/weekend, and mean traffic speed. For evacuation period traffic prediction, we used evacuation demand related features such as the time left before landfall, distance from the nearest evacuation zones for each detector, and cumulative population under mandatory evacuation orders in the transfer-learned DGCN-LSTM model. We collected declaration time of evacuation orders from different County Emergency Managements' official Twitter posts and counted total number of people living in respective County's evacuation zones to generate 'population under mandatory evacuation order' variable. We also used human movement inflow and outflow values for each detector from the Facebook movement data.

RESULTS

Regular Period Traffic Prediction

We implemented the prediction model by using Python's Pytorch environment (*Pytorch*, 2016). For regular period traffic prediction, we discarded evacuation demand related features. We used 90% data for training, 5% for validation, and 5% data to test model performance. To train the model, we used ADAM optimizer and assigned mean squared error as loss functions. To compare different models' performance, we considered several loss criteria such as Root Mean Square Error **(RMSE)**, Mean Absolute Error **(MAE)**, Mean Absolute Percentage Error **(MAPE)**, and $\boldsymbol{R^2}$ value. Equations for loss criteria are provided in **(Eq. 6 – 8)**. Here, $F_{actual,i}$ denotes the actual traffic flow at timestep i, and $F_{predicted,i}$ is the predicted traffic flow at timestep i.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(F_{actual,i} - F_{predicted,i}\right)^2} \qquad (6)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|F_{actual,i} - F_{predicted,i}\right| \qquad (7)$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{F_{actual,i} - F_{predicted,i}}{F_{actual,i}}\right| \qquad (8)$$

For regular period traffic prediction, we compared the performance of proposed DGCN-LSTM model against several baseline models such as LSTM, CNN-LSTM, and GCN-LSTM. We first trained all models without adding the Facebook movement data. All models achieved similar R^2 values (95%). DGCN-LSTM model achieved lowest RMSE values of 356.47 and MAPE of 8.74 compared to other baseline models. Then, we extracted baseline movement by considering day of the week and hour to generate inflow and outflow values for all detectors in the regular period. After adding Facebook baseline movement data, the RMSE values further decreased for all models. DGCN-LSTM model outperformed other baseline models with the lowest RMSE values of 319.91 and MAPE of 7.46. **Table 2** presents average model performances after running 10 times and impact of Facebook movement data on prediction performance. DGCN-LSTM outperformed other baseline models during regular period, and addition of Facebook movement data increased all models' performances.

Evacuation Period Traffic Prediction

In case for evacuation period traffic prediction, we first used only non-evacuation related features to predict evacuation traffic. Like regular period traffic prediction, we compared the effect of adding Facebook movement data on all models' performances. We used 80% data for training, 10% for validation and 10% data to test model performance. We used ADAM optimizer and mean squared error as loss function. **Table 3** shows average model performances after running 10 times during evacuation period. As shown in **Table 3**, all models performed poorly. However, the result is intuitive since regular period traffic patterns differ significantly from evacuation period traffic. RMSE values for all models were more than 1000 even after adding the Facebook movement data. However, the DGCN-LSTM model still performed better than other models in this scenario with RMSE value of 1084.36 and R^2 value of 0.55. Moreover, after adding the Facebook data, overall performance of all models slightly improved. The RMSE value of the LSTM model decreased to 1325.69 from 1328.72; the R^2 value of LSTM also increased from 32% to 33%. The RMSE value of CNN-LSTM model decreased from 1180.63 to 1134.51, and R^2 value also increased from 46% to 50%. Similar to previous cases, DGCN-LSTM model trained with Facebook movement data outperformed other models with RMSE value of 1053.24 and R^2 value of 0.57.

Next, to improve the DGCN-LSTM model's predictability during evacuation period, we applied a transfer learning approach proposed by (Rahman & Hasan, 2023). We used a pretrained DGCN-LSTM model by using evacuation period traffic state as input. The pretrained model contained information on how the detectors were connected in the transportation network and the traffic flows between different detectors. Additionally, we trained another neural network with **evacuation demand related features** to capture temporal dependency of evacuation traffic. In this modeling architecture, a control layer is used, to control relevant information (such as network connectively, flow propagation pattern etc.,) transfer from regular period traffic to evacuation period traffic. By adopting the transfer learning technique, the RMSE values of DGCN-LSTM model decreased to 514.20 when Facebook data were not used, and the R^2 value increased from 0.55 to 0.89 as given in **Table 3**. After adding Facebook movement data to the transfer-learned DGCN-LSTM model, the RMSE value further reduced to 393.28 and the R^2 value increased from 0.57 to 0.93. The transfer-learned DGCN-LSTM model trained with Facebook data outperformed other baseline models. **Table 3** illustrates the benefits of using transfer learning approach along with Facebook movement data to predict evacuation period traffic during a rapidly intensifying hurricane with higher accuracy.

DISCUSSIONS

In the study, we present a deep learning model to predict traffic during hurricane evacuation. We integrate both traffic detector data and Facebook movement data to the proposed DGCN-LSTM architecture. Both regular period and evacuation period traffic predictions achieve higher accuracy when Facebook movement data are used. After applying the transfer learning approach, the proposed model predicts evacuation period traffic up to 6 hours in advance with 93% accuracy. **Fig. 12** shows the correlation between actual traffic and predicted traffic of transfer learned DGCN-LSTM model when Facebook movement data is not utilized. The model achieves 89% accuracy and RMSE value of 514.20. When Facebook movement data are used, the transfer-learned DGCN-LSTM model learns the evacuation period traffic patterns very well as actual and predicted traffic almost matched with each other. **Fig. 13** shows the correlation between actual and predicted traffic flow when Facebook movement data are utilized.

We also plot the detector wise variations of actual and predicted traffic flows without Facebook movement data (see **Fig. 14**); the symmetric mean absolute percentage error **(SMAPE)** values for different prediction horizons remain less than 13%. When Facebook movement data are used (see **Fig. 15**), the SMAPE values for different prediction horizons decrease to less than 6%. It indicates that the model can better capture the spatiotemporal patterns of evacuation demand when Facebook movement data are used along with traffic detector data. The equation of SMAPE is provided in **(Eq. 9).**

$$SMAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{|F_{actual,i} - F_{predicted,i}|}{(|F_{actual,i}| + |F_{predicted,i}|)/2} \qquad (9)$$

The transfer-learned DGCN-LSTM model can also be used to visualize the network-wide congestion propagation. **Fig. 16** shows the actual traffic flow from RITIS from September 26, 4 am – 9 am. There was heavy traffic flow in I-75, I-4, and I-95 interstates. During this time, several counties ordered evacuation orders which caused higher traffic flow in I-75 and I-4 interstates. The prediction model captures the network-wide traffic flow very well for different prediction horizons as shown in **Fig. 17.** The visualization capabilities of the DGCN-LSTM model will help evacuation traffic managers to take proactive decisions in real time by providing early information of how future traffic congestion may look like in the transportation network.

The proposed model provides useful information regarding traffic flow patterns during hurricane evacuations, and it aids for developing an effective evacuation planning and decision-making system. The prediction capabilities of the developed model enable emergency managers to forecast congestion hotspots and traffic patterns, allowing for more prompt decisions and activation of strategies. With this foresight, authorities can take proactive steps to reduce traffic congestion, optimize evacuation preparations, and ensure inhabitants' safety and well-being in hurricane-prone areas.

Because the model can forecast traffic conditions ahead of time, evacuation traffic managers are better equipped to anticipate surges in traffic demand and modify evacuation plans as circumstances change such as change of hurricane path/intensity or issuance of new evacuation orders. Traffic managers can plan for activating traffic management strategies such as emergency shoulder use or contra flow based on anticipated traffic condition. They can also decide the timing and duration of such traffic management strategies.

For emergency managers, network-level traffic flow prediction can allow improving evacuation procedures. They can improve evacuation procedure by strategically allocating resources to areas that are most in need. For instance, emergency managers can identify potential congestion points in advance. They can reroute all vehicles used by emergency response teams to avoid these congestion-prone areas and reach critical locations without delay. This can be done by accurately forecasting traffic flow patterns in the road network. Furthermore, the proposed framework can mitigate several risks associated with an evacuation plan that can hinder timely evacuation process. For example, people may not access evacuation routes due to heavy traffic on the network. Traffic planners can identify capacity issues of current evacuation routes and propose more effective evacuation routes for future evacuations.

The proposed framework has the potential to significantly increase the resilience and effectiveness of evacuation traffic management in hurricane-prone regions. It improves the predictive capacities to forecast evacuation traffic flow, allowing for proactive decision-making based on real-time information.

CONCLUSIONS

In this study, we use a deep learning-based traffic prediction model named DGCN-LSTM to predict traffic during a rapidly intensifying hurricane. The proposed model utilizes traffic detector data and Facebook movement data to predict traffic up to 6 hours in advance. The movement data provides spatio-temporal movement distributions at a high spatial resolution. Evacuation movements increased in Central Florida during Hurricane Ian's evacuation period. Movement data also shows that people evacuated from Florida's west coast to the Central Florida region through Interstate I-4 (Eastbound). The movement data contains information regarding increased human movement through the transportation network, and it is representative of actual traffic flow in the network. The performance of the traffic prediction model significantly improves by incorporating the information from Facebook movement data. It increases the performance of the transfer-learned DGCN-LSTM model from $R^2 = 0.89$ without using Facebook data to $R^2 = 0.93$ when Facebook data is used.

The study also deals with the challenge of data unavailability and illustrates how to develop a traffic prediction model by incorporating discontinuous Facebook movement data via randomly selected index numbers. Traffic management agencies can use the data-driven model trained with Facebook movement data to predict traffic congestions in advance, take proactive measures to reduce traffic delays and improve the efficiency of evacuation process. As the model incorporates real-time detector and social media data, agencies can also implement it to identify vulnerable zones with high congestion probabilities earlier when hurricane unfolds in real time.

There are several limitations of this study. Due to data scarcity, we only use 16 hours of daily movement data. So, the approach needs further investigation with additional data from multiple hurricanes to develop a more generalized model and improve the robustness of the model against sudden demand surge. We also use cumulative population under mandatory evacuation orders as input features. The model performance should be evaluated if actual population under mandatory evacuation orders can be obtained to have more realistic evacuation related features. Additionally, Florida Department of Transportation (FDOT) implemented emergency shoulder use or ESU (Florida Department of Transportation, 2022) on the eastbound direction of I-4 (from Mile Marker 3 to Mile Marker 63) starting at 5:20 PM on 9/27/2022 and ending at 1:14 AM on 9/28/2022 (O. Faruk, personal communication, June 2, 2024). This time period overlaps with a small portion of our training data (1 hour 40 minutes out of 32 hours). Traffic detectors are not designed to record vehicles running on road-side shoulders, these vehicles are not included in our dataset. Other interstates and westbound direction of I-4 did not have flows on shoulders. It is a data-related issue, and the developed framework can also predict vehicles running on shoulders if proper data can be obtained from traffic detectors.

DATA AVAILABILITY STATEMENT:

The test dataset used in the study is available in the following repository in accordance with funder data retention policies. The train dataset and code that support the findings of this study are available from the corresponding author upon reasonable request.

(https://www.designsafe-ci.org/data/browser/public/designsafe.storage.published/PRJ-4268)

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FIGURE CAPTION LIST:

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TABLES:

Table 1. Input features

Non-evacuation related features	Evacuation demand related features	Facebook movement features
Detector Id	Time left before landfall	Human inflow to a traffic detector
Time periods (early morning, morning, mid-day, evening)	Cumulative population under mandatory evacuation orders	Human outflow from a traffic detector
Weekday or Weekend	Distance from nearest evacuation zones	-
Traffic flow at current time t	-	-
Previous day mean traffic flow	-	-
Previous period mean traffic flow	-	-
Previous day standard deviation of traffic flow	-	-
Previous period standard deviation of traffic flow	-	-
Mean speed over an hour	-	-

Table 2. Model performances for regular period traffic prediction

Model	Without Facebook Data				With Facebook Data			
	RMSE	MAE	MAPE	R^2	RMSE	MAE	MAPE	R^2
LSTM	374.76	227.58	9.53	0.95	343.29	196.24	8.45	0.96
GCN-LSTM	374.73	220.16	9.28	0.95	343.24	195.68	8.08	0.96
CNN-LSTM	368.37	217.03	8.84	0.95	339.02	194.79	8.06	0.96
DGCN-LSTM	356.47	215.63	8.74	0.95	319.91	186.19	7.46	0.96

Table 3. Model performances for evacuation period traffic prediction (minimum flow 50.0 and maximum flow 9977.45)

Model	Without Facebook Data				With Facebook Data			
	RMSE	MAE	MAPE	R^2	RMSE	MAE	MAPE	R^2
LSTM	1328.72	962.72	93.08	0.32	1325.69	949.17	92.43	0.33
GCN-LSTM	1183.41	802.02	92.50	0.45	1155.02	758.32	91.75	0.48
CNN-LSTM	1180.63	798.67	92.15	0.46	1134.51	756.05	88.98	0.50
DGCN-LSTM	1084.36	746.18	82.94	0.55	1053.24	748.48	73.51	0.57
DGCN-LSTM (transfer learned)	514.20	328.98	23.84	0.89	393.98	276.32	13.49	0.93

Fig. 1. Selected detector distribution from RITIS

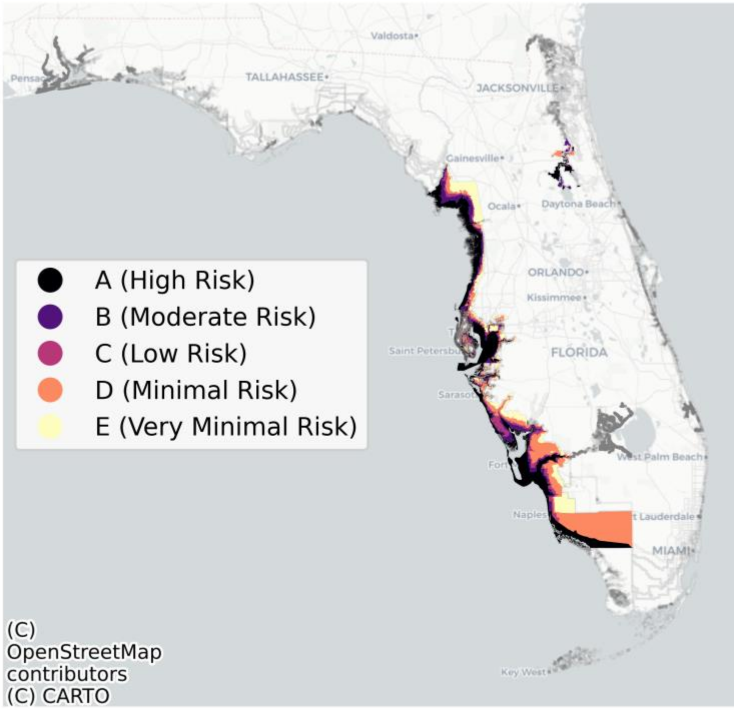

Fig. 2. Mandatory evacuation zones during Hurricane Ian

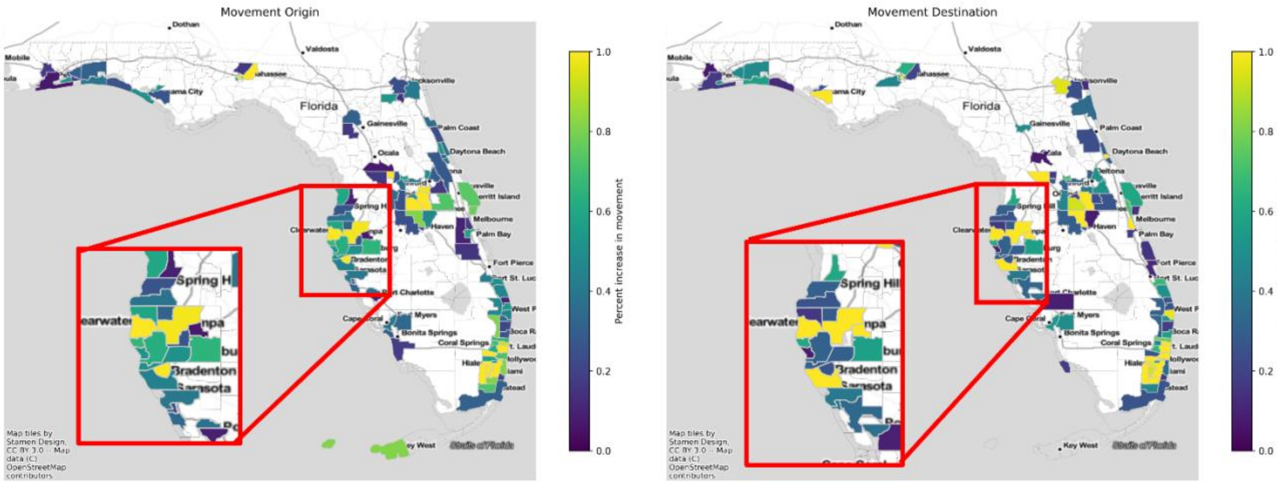

Fig. 3. (Left) Origins of movements; (right) destinations of movements during September 26 (3 am-11 am)

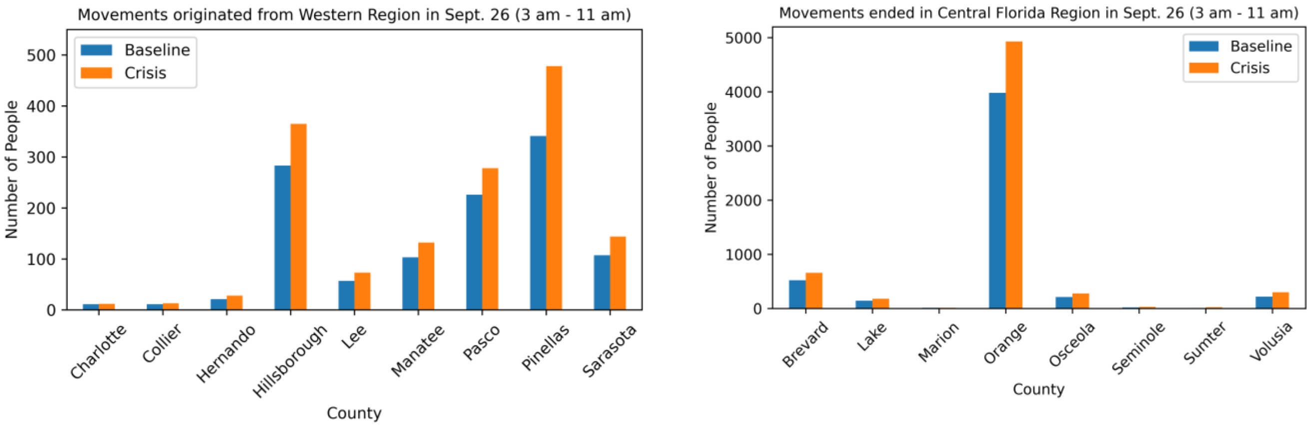

Fig. 4. (Left) Origins of movements from western region of Florida; (right) destinations of movements towards central Florida region during September 26 (3 am-11 am)

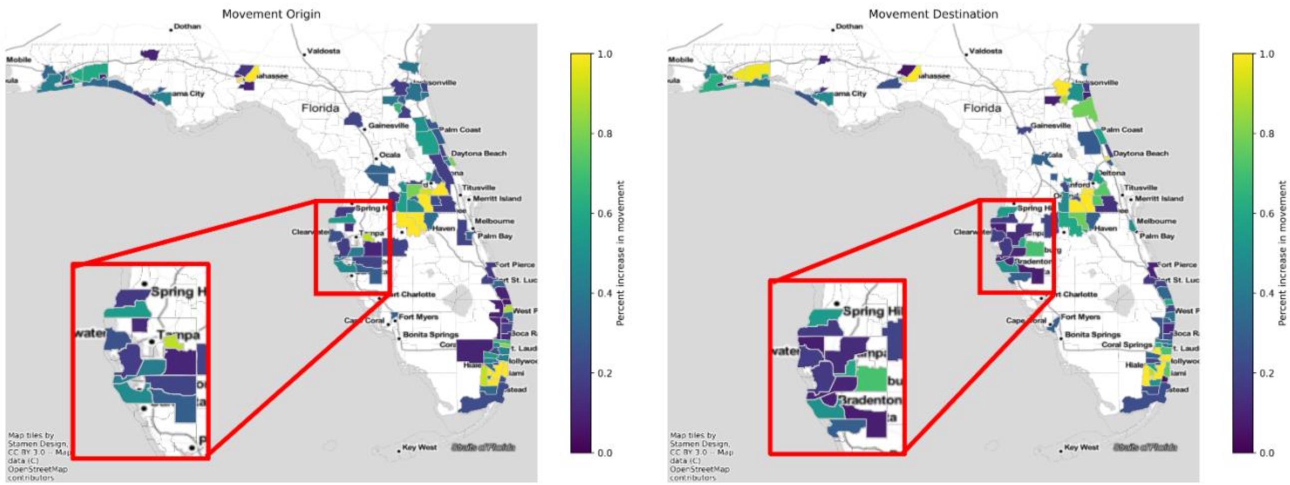

Fig. 5. (Left) Origins of movements; (right) destinations of movements during September 27 (3 am-11 am)

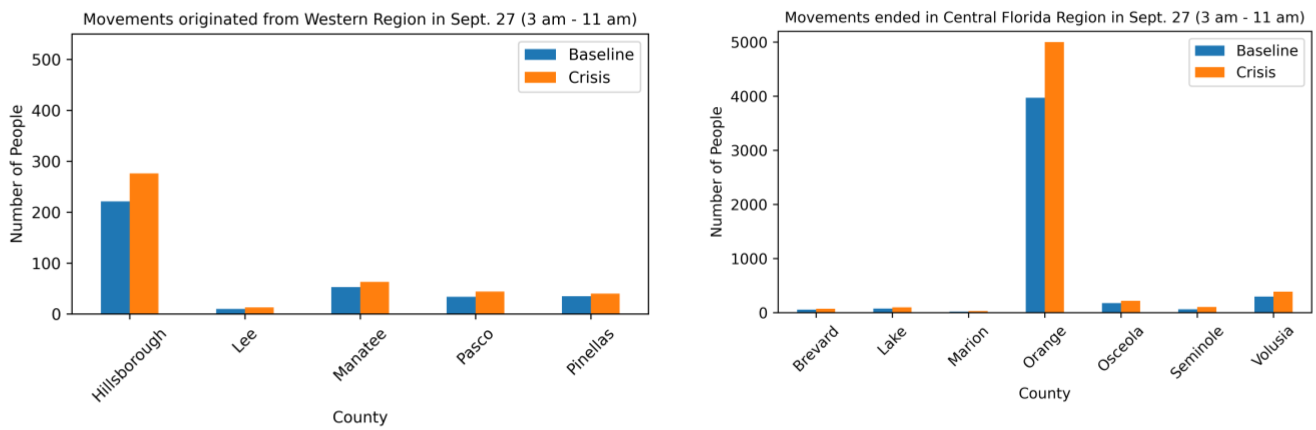

Fig. 6. (Left) Origins of movements from western region of Florida; (right) destinations of movements towards central Florida region during September 27 (3 am-11 am)

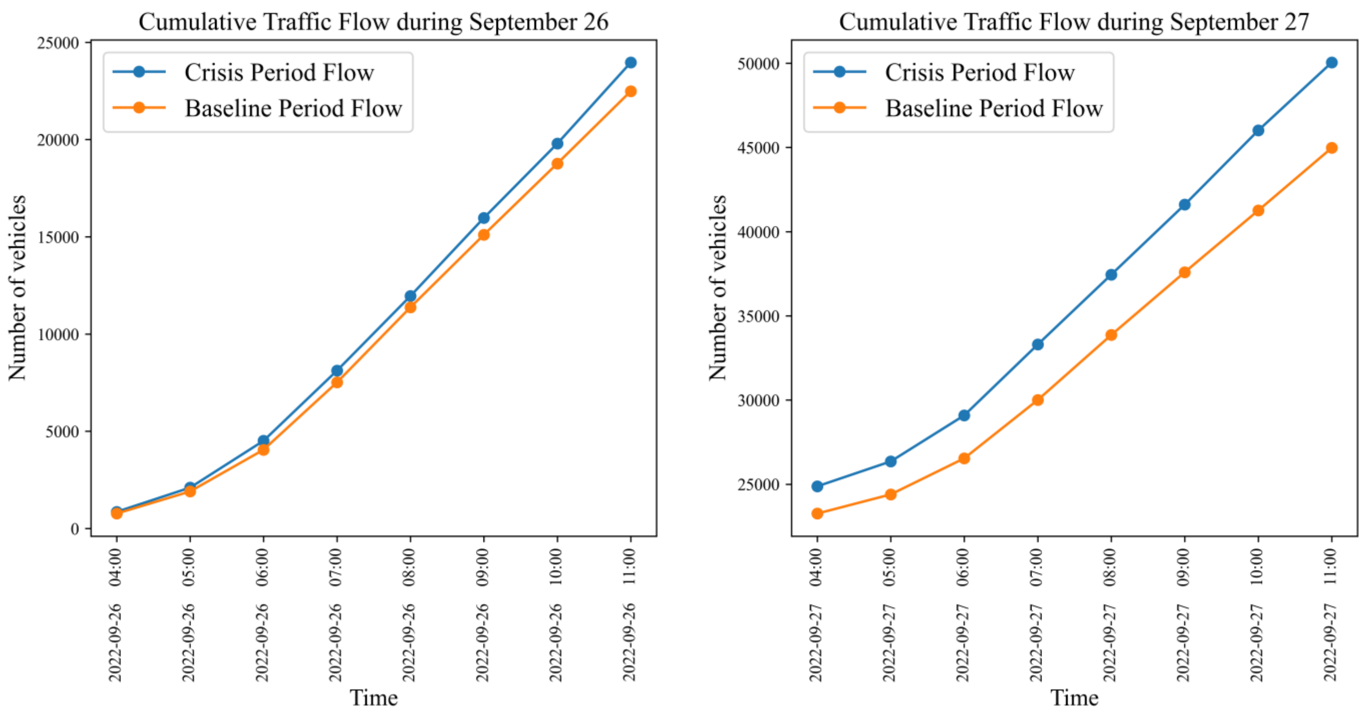

Fig. 7. Eastbound cumulative traffic flow on an I-4 detector

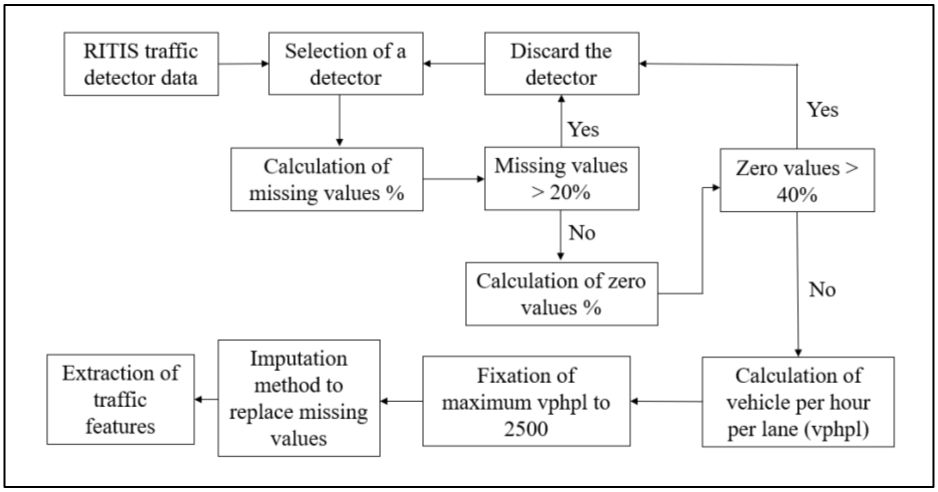

Fig. 8. Processing of traffic detector data

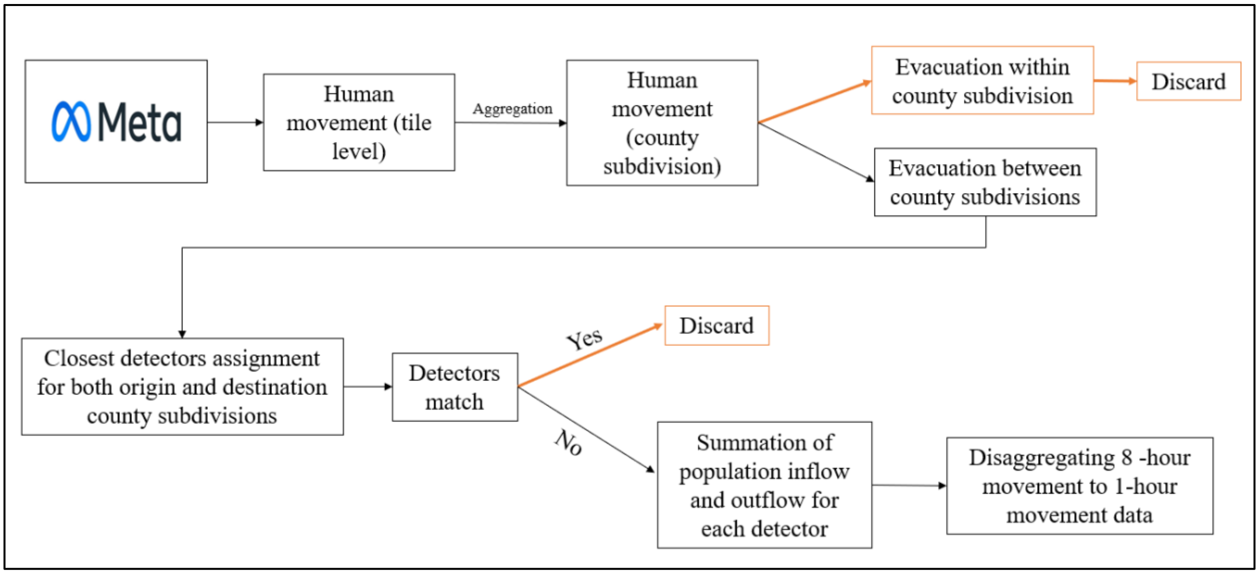

Fig. 9. Processing of Facebook movement data

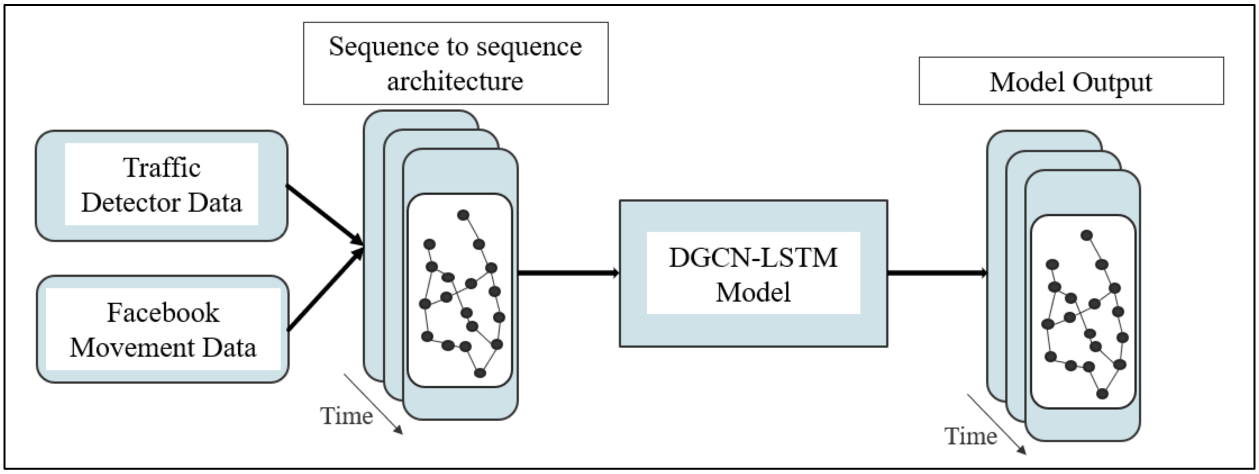

Fig. 10. Framework of the DGCN-LSTM model

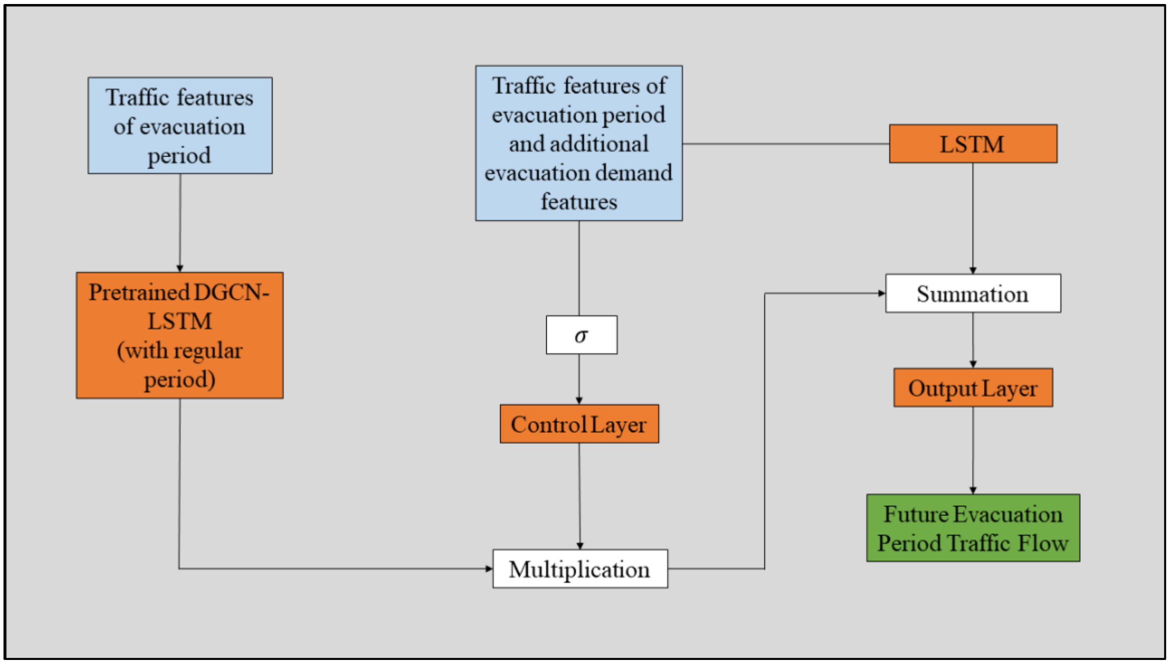

Fig. 11. Transfer learning approach for evacuation period traffic prediction

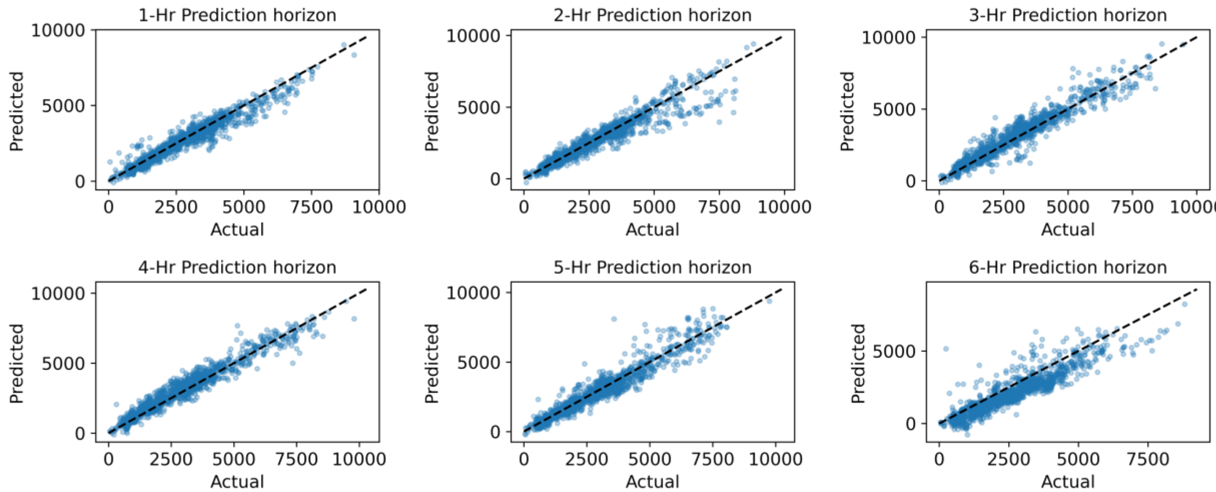

Fig. 12. Correlation between actual traffic and predicted traffic for 6-hour time horizon (when Facebook movement data is not used)

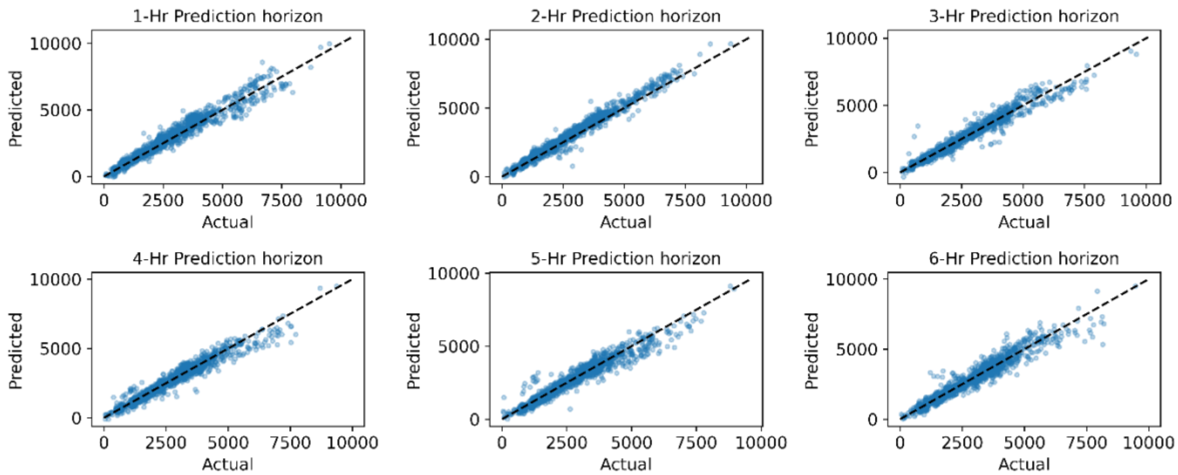

Fig. 13. Correlation between actual traffic and predicted traffic for 6-hour time horizon (when Facebook movement data is used)

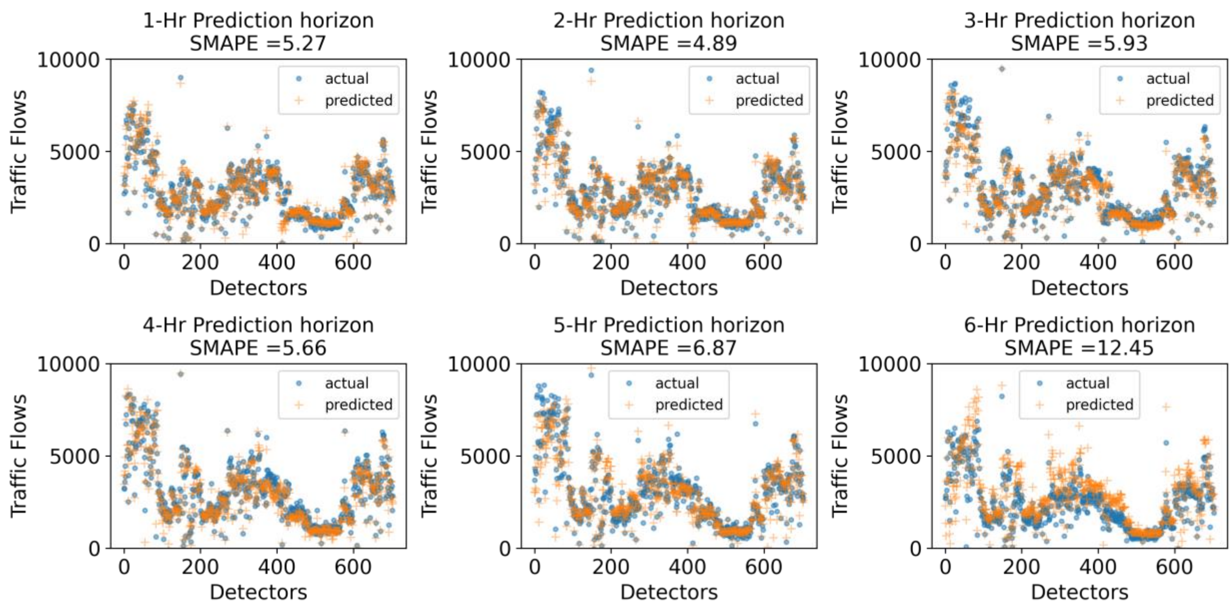

Fig. 14. Detector wise actual flow vs. predicted flow with SMAPE values (without Facebook movement data)

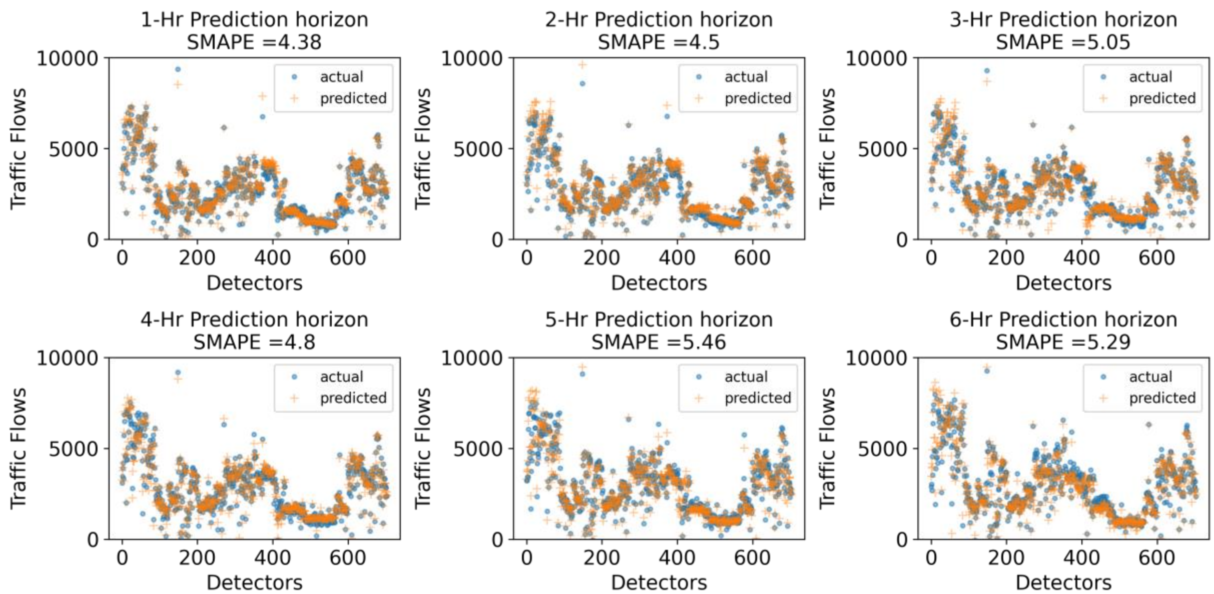

Fig. 15. Detector wise actual flow vs. predicted flow with SMAPE values (with Facebook movement data)

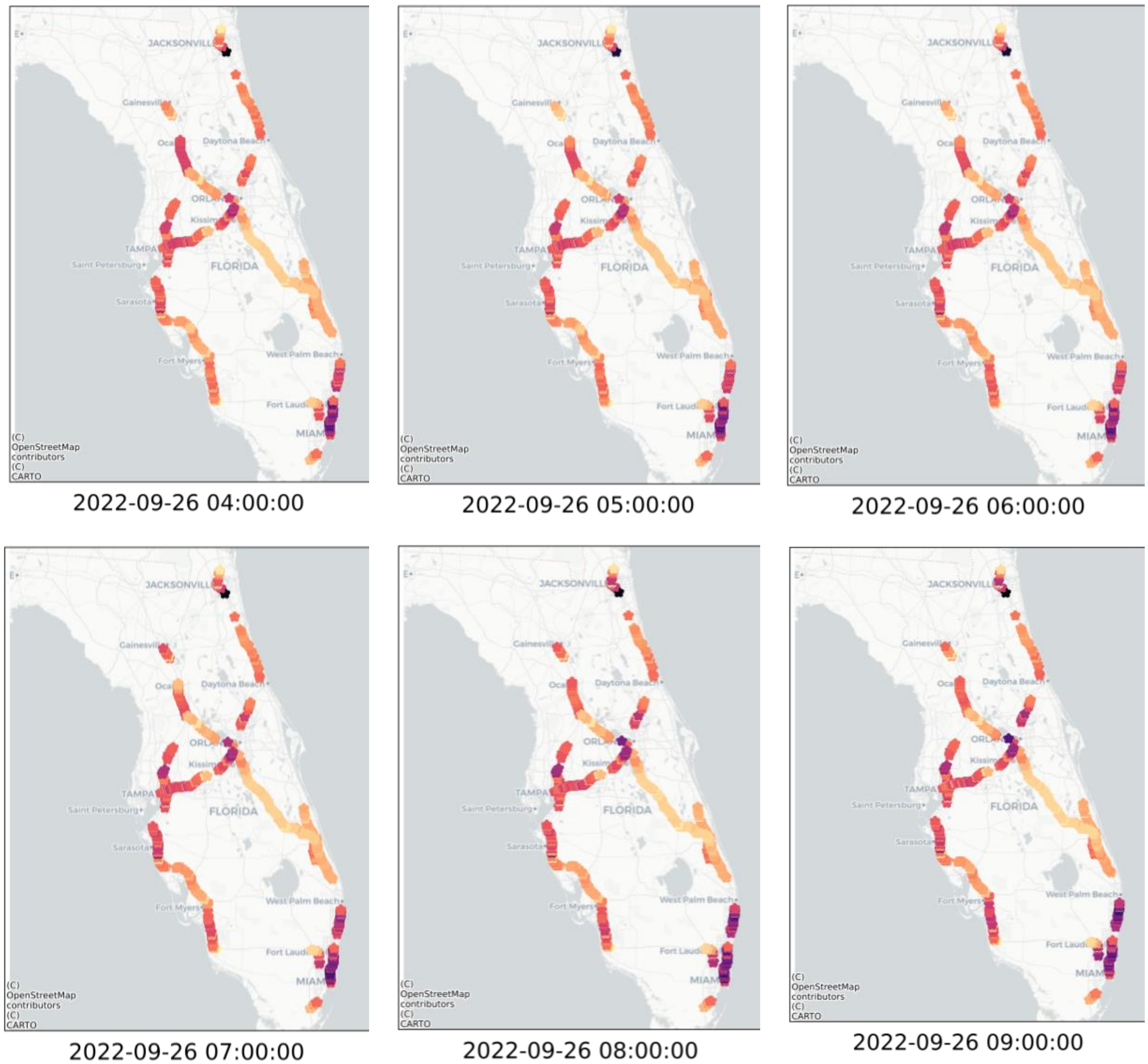

Fig. 16. Congestion propagation visualization of actual traffic flow (vertical color bar denotes traffic flow)

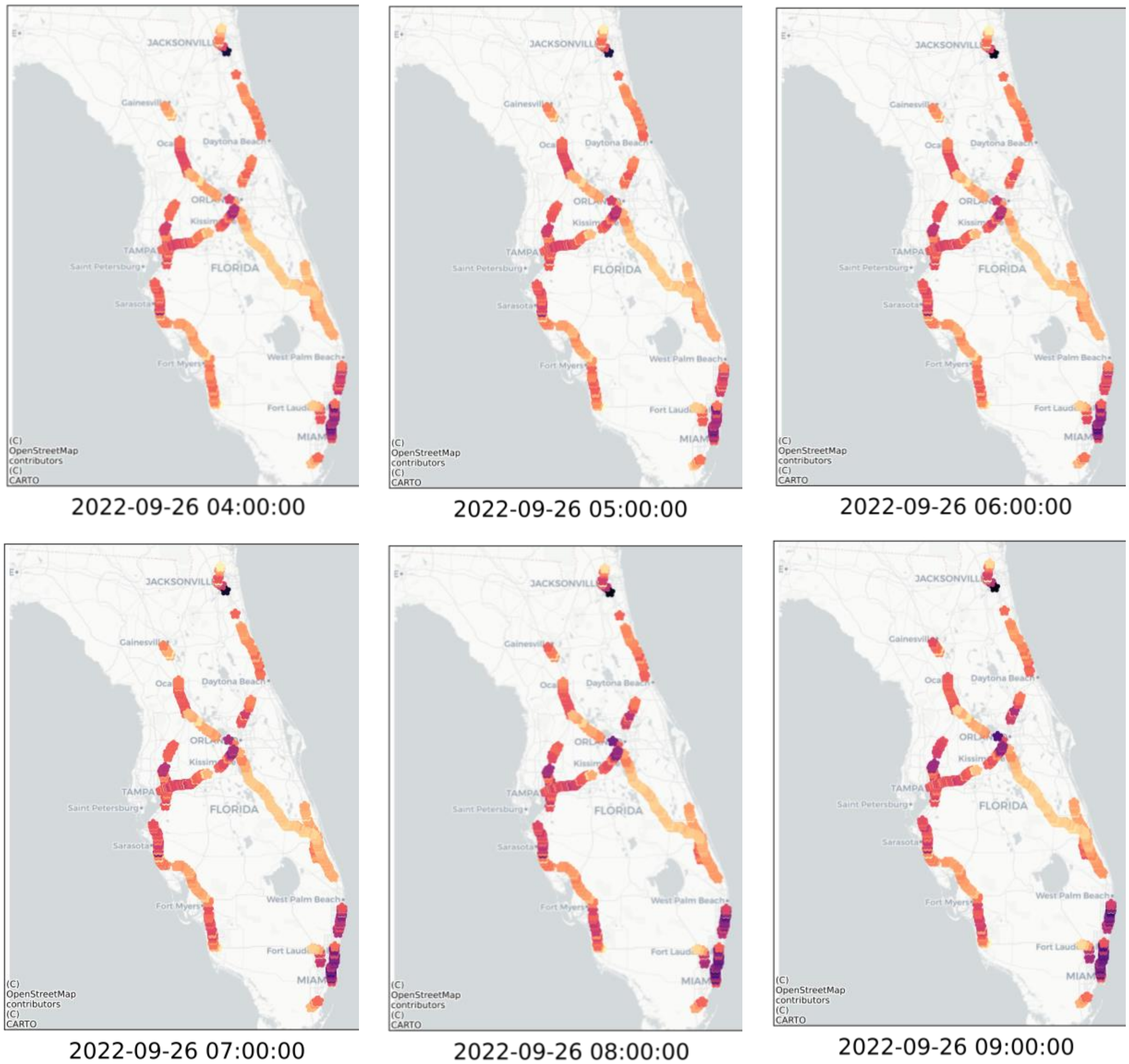

Fig. 17. Congestion propagation visualization of predicted traffic flow (vertical color bar denotes traffic flow)