

A Deep Learning Approach for Network-wide Dynamic Traffic Prediction during Hurricane Evacuation

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Abstract—Proactive evacuation traffic management largely depends on real-time monitoring and prediction of traffic flow at a high spatiotemporal resolution. However, evacuation traffic prediction is challenging due to the uncertainties caused by sudden changes in projected hurricane paths and consequently populations' evacuation behavior. Moreover, modeling spatiotemporal traffic flow patterns requires extensive data over a longer time period, whereas evacuations typically last for two to five days. In this paper, we present a novel data-driven approach for predicting evacuation traffic at a network scale. We develop a dynamic graph convolutional long short-term memory neural network (DGCN-LSTM) model to learn the network dynamics during hurricane evacuation. We first train the model for non-evacuation period traffic data and found that the model outperforms existing deep learning models for predicting non-evacuation period traffic with an RMSE value of 226.84. However, when the model is applied for predicting evacuation traffic, the RMSE value increased to 1440.99. We overcome this issue by adopting a transfer learning approach with additional features related to evacuation traffic demand such as distance from the evacuation zone, time to landfall, and other zonal level features to control the transfer of information (network dynamics) from non-evacuation periods to evacuation periods. The final transfer learned DGCN-LSTM model performs well to predict evacuation traffic flow (RMSE=399.69). The implemented model can be applied to predict evacuation traffic over a longer forecasting horizon (up to 6-hour). It will assist transportation agencies to activate appropriate traffic management strategies to reduce delays for evacuating traffic.

Index Terms— artificial intelligence, network modeling, transfer learning, traffic prediction, spatiotemporal traffic pattern, evacuation traffic management

1. Introduction

Hurricanes have become more intense and frequent due to climate change and other related reasons (Tom Knutson, 2022). Coastal populations of the United States are becoming more vulnerable to the impact of hurricanes (Park, 2021). To save lives and reduce suffering of people during such events, emergency management agencies need efficient and pro-active strategies to ensure timely evacuation. Evacuation traffic management has been a major concern for transportation agencies and policy makers (House of Representatives Florida, 2018). The concern has grown further after the disastrous impact of Hurricane Irma in 2017 when about 6 million residents of Florida (29.3% of the population) evacuated from major cities including Key West, Miami, and Tampa (Northeast Florida Regional Planning Council, 2021). With only two major interstate highways (I-75 and I-95) available for leaving Florida, the evacuation caused significant traffic congestion and crashes on highways (Rahman et al., 2021a), thus affecting the physical and mental health of evacuees.

Efficient evacuation traffic management requires an effective evacuation plan that includes proactive measures to overcome unexpected events such as traffic incidents or a change of hurricane path causing unexpected demand surge etc. Over the past decades, several traffic management strategies (Murray-Tuite et al., 2017; Murray-Tuite and Wolshon, 2013) such as emergency shoulder use, contraflow operations, traffic signal control, route guidance etc. have been proposed to alleviate congestion during evacuation. However, a proactive deployment of these measures requires a better understanding of prevailing traffic conditions and prediction of

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future traffic for a long-term horizon (> 1 hour). Thus, one of the critical aspects of evacuation traffic management is to understand the spatial and temporal distribution of congestion and to reliably predict future traffic condition. Based on this information, traffic managers can decide where, when, and for how long a strategy should be deployed to reduce delays.

Previous studies (Barrett et al., 2000; Chen et al., 2020; Li et al., 2006; Murray-Tuite and Wolshon, 2013) have adopted mathematical modeling and simulation-based approaches to predict evacuation traffic. However, these approaches are not robust enough against sudden demand surge associated with irregular traffic flow patterns during evacuation. Moreover, developing such a model for a large-scale network is complicated since it relies on assumptions such as user equilibrium for an analytical approach or a detailed representation of traffic networks for a simulation-based approach. Due to such complexities, it takes a substantial amount of time to produce a stable solution predicting traffic at a network scale, making these models less suitable for a real-time application. Ubiquitous use of traffic sensors can provide a viable solution for overcoming these issues by developing data-driven network models.

In this context, a data-driven network-scale model can be developed for real-time traffic prediction. For example, in Florida almost all the interstate highways are equipped with microwave radar-based traffic detectors owned by Florida Department of Transportation (FDOT) (<https://www.fdot.gov/>). These detectors monitor high-fidelity real-time traffic data that can reveal spatio-temporal patterns of evacuation traffic in response to unexpected events. Although roadway detectors have widely been deployed in major highways in the USA, few studies have utilized the data available from these detectors for network-level evacuation traffic analysis and prediction (Ghorbanzadeh et al., 2021; Staes et al., 2021).

One of the major challenges towards developing a data-driven modeling framework is that such a framework needs to deal with the high dimensionality of the data due to spatiotemporal dependency among traffic variables and capture congestion propagation in the network. Recent advances in neural computation such as deep learning models have created an opportunity to deal with such high dimensionality in traffic data. Moreover, these models utilize the concept of graph theory to represent congestion propagation in a large-scale traffic network (Cui et al., 2020b, 2020a; Guo et al., 2020; Peng et al., 2021, 2020). For instance, state-of-the-art graph convolutional neural networks use network structure (i.e., node-link relationship) to capture flow propagation inside the network and the cross-correlation among traffic states. However, existing graph convolutional approaches do not represent the actual dynamic nature of a transportation network such as how travel time changes over time and thereby influencing the changes in traffic flow patterns. Another issue with such a network-wide model is that it needs an extensive amount of data to train the model to make a reliable prediction. Thus, it is not feasible to develop such a model for special events such as hurricane evacuation, where traffic data are available only for a few days.

In this study, we develop a novel deep learning architecture to overcome these challenges for evacuation traffic prediction. First, we develop a dynamic graph convolutional long short-term memory neural network (DGCN-LSTM) model with contextual understanding of congestion propagation inside the network. To overcome the limitation of data scarcity and model overfitting issue, we train the model on regular period traffic data collected from May 2017 to August 2017. Later, we transfer this model to an evacuation period with an additional neural network block as a controller to predict traffic during evacuation period. The evacuation period data were collected

from September 4, 2017 to September 9, 2017 covering the evacuation period of Hurricane Irma. The controller uses evacuation travel demand features such as distance from the evacuation zone, time to landfall, and other zonal level features to control which information from the DGCN-LSTM to be included to predict traffic during evacuation period. As such, the final evacuation prediction model has the contextual understanding of congestion propagation inside the network; at the same time, it can discard any unnecessary information such as seasonality in traffic patterns which might be out of context during an evacuation period.

This study has made several contributions for evacuation traffic prediction using large-scale traffic detector data:

- It collects and analyzes large-scale traffic detector data during Hurricane Irma's evacuation, providing insights on network wide spatiotemporal patterns of evacuation traffic.
- It identifies the challenges to deal with large-scale real-time traffic data for evacuation traffic analysis and prediction.
- It develops a dynamic graph convolutional neural network model to learn the congestion propagation for a large-scale network.
- It implements a transfer learning based deep learning architecture to incorporate evacuation context for improving the performance of evacuation traffic prediction.

2. Literature Review

2.1 Evacuation Traffic Modeling

Evacuation traffic management can significantly benefit from how accurately we can predict traffic in real time. However, practices in evacuation traffic management mostly rely on behavioral analysis of evacuees to understand and predict evacuation decisions (Moynihan and Fonseca, 2016; Murray-Tuite et al., 2018; Murray-Tuite and Wolshon, 2013; Sadri et al., 2013a; Wong et al., 2018). For instance, many studies investigated hurricane evacuation behavior focusing on understanding the factors related to evacuation decisions (Fry and Binner, 2015; Gudishala and Wilmot, 2013; Hasan et al., 2013, 2011; Huang et al., 2016), mobilization time (Sadri et al., 2013b), departure time (Pel et al., 2012; Rambha et al., 2019), and destination choice (Mesa-arango et al., 2013; Wilmot et al., 2006). To predict evacuation traffic demand, previous studies adopted such individual- or household-level decision-making models (Blanton et al., 2020; Davidson et al., 2020; Gudishala and Wilmot, 2012; Wilmot et al., 2006; K. Yang et al., 2019). These approaches, however, depend on survey data that are expensive and difficult to collect as a hurricane unfolds in real time. Several studies have analyzed evacuation traffic patterns using real-time data, but these studies were limited to only understanding operational performance of highways during evacuation (Dixit and Wolshon, 2014; Ghorbanzadeh et al., 2021; Litman, 2006; Staes et al., 2021).

A major challenge in modeling evacuation traffic arises from the fact that traffic patterns during evacuation, characterized by higher demand and traffic congestion, significantly differ from traffic patterns in a non-evacuation period (Rahman et al., 2021b). Evacuation traffic demand is more uncertain due to sudden changes in hurricane paths (Rahman et al., 2021c). To model such uncertain demand variations, we need a demand responsive model that hardly exists in the literature. A few studies (Chen et al., 2020; Li et al., 2006) have adopted mathematical modeling and simulation-based traffic assignment approaches to model evacuation traffic demand. However, such approaches rely on certain assumptions (e.g., user equilibrium, fixed O-D patterns) which may fail to represent an actual evacuation scenario. A data-driven method can offer an alternative

solution to overcome this issue. In recent years, a few studies have adopted data-driven methods for traffic prediction during hurricane evacuation (Rahman and Hasan, 2018; Roy et al., 2021). However, these studies developed models for a specific segment and those models are not generalized for the entire network. Moreover, when predicting future traffic, those models do not consider spatial correlations among traffic states. Hence these methods are not applicable for traffic prediction at the level of a network.

2.2 Application of data-driven methods for network level traffic modeling

A data-driven approach predicts future traffic states from historical traffic patterns, without making any assumption on user behavior (Oh et al., 2017), leading to a more robust and demand responsive model compared to traditional traffic prediction models. Recently, data-driven approaches are gaining more attention mainly for three reasons: first, model-driven approaches are more time consuming compared to typical data-driven approaches for calibrating the required parameters; second, an extensive coverage of sensors over transportation networks, fueled by data processing technologies and computational power, has created an opportunity to build big data approaches; third, data-driven approaches do not rely on assumptions on user behavior, hence they are more applicable for real-world dynamic problems. Data-driven methods have been applied in numerous traffic prediction contexts such as traffic speed prediction (Cui et al., 2020a, 2018b; Epelbaum et al., 2017; Ma et al., 2015; Zhao et al., 2020), travel time prediction (Yanjie Duan et al., 2016), traffic flow prediction (Guo et al., 2021; Luo et al., 2019; Polson and Sokolov, 2017; B. Yang et al., 2019), and vehicular queue length prediction (Lee et al., 2019; Rahman and Hasan, 2021).

Previous studies developed traditional data-driven models for traffic prediction such as Support Vector Machine (SVM) (Ahn, 2016; Wu et al., 2004), K-Nearest Neighbor (KNN) (Cai et al., 2016; Habtemichael and Cetin, 2016; Meng et al., 2015; Myung et al., 2011; Qiao et al., 2013; Yu et al., 2016), and Artificial Neural Network (ANN) (Innamaa, 2005; Lee, 2009; Park et al., 1999; Yu et al., 2008). These studies were limited in scope and applicable for traffic prediction at a small spatial scale such as for a roadway segment or an intersection. Recently, to predict traffic at a network scale, many studies have applied deep neural network-based approaches such as Long Short-Term Memory Neural Network (LSTM), Convolutional Neural Network (CNN), Graph convolutional Neural Network (GCN) and integrated version of these models such as Convolutional LSTM (ConLSTM) and Graph Convolutional LSTM (GCNLSTM) (Atwood and Towsley, 2015; Cui et al., 2018a; Li et al., 2018a; Zhao et al., 2020). However, these studies mainly focused on learning traffic representation at a network scale, instead of learning network flow dynamics—how travel time variation impacts traffic flow propagation in a network.

A few studies have applied graph convolution-based approaches to dynamically learn spatiotemporal features of a transportation network (Guo et al., 2020; Peng et al., 2021, 2020). But these studies are limited to exploring different graph representation techniques such as learning latent network Laplacian matrix, constructing roadways inflow outflow probability matrix and weighted incident matrix to represent dynamic traffic patterns. In the first study, using a dynamic graph convolution approach, Guo et al. (Guo et al., 2020) developed a method to predict the time variant Laplacian matrix to represent the network flow propagation from one node to another node. Later, Peng et al. (Peng et al., 2021, 2020) represented the dynamics of a network based on time variant inflow and outflow probabilities.

In addition, Guo et al. and Tang et al (Guo et al., 2019; Tang et al., 2020) applied an attention based spatial-temporal graph convolutional approach for traffic prediction. In the attention-based approach, the graph adjacency matrix is multiplied with correlation factors. These correlation factors are estimated based on capturing the similarity between traffic states of two different nodes and assigned as weights for the adjacency matrix. However, in the traffic prediction problem, the graph convolution neural network itself captures the spatial cross correlation among neighboring nodes of a transportation network. In this context, an attention-based graph convolutional approach would model the correlations twice requiring more learnable parameters, compared to directly learning spatial cross correlation using only a graph convolutional approach. In our study, we applied domain knowledge to represent network dynamics through creating a dynamic graph, thus reducing the number of learnable parameters.

None of these studies have considered the influence of travel time variation on changes in traffic propagation; they have not considered the fact that at a given time interval whether traffic will reach from an origin to a destination depends on the travel time of the associated routes. On the contrary, this study develops a method to learn the dynamics of a transportation network by capturing the correlation between travel time variations and traffic flow propagation. Rather than using inflow and outflow probability values as weights or randomly predicting the weights for different origin to destination (OD) pairs, we define the weights based on travel time to represent network dynamics. Hence, our time variant dynamic graph represents the travel time variations of the network.

Moreover, developing such a large-scale model requires extensive data which makes it unsuitable for a real-world deployment in managing special events such as traffic incident and evacuation traffic management. Recently, Peled et al (Peled et al., 2022) tested the transferability of traffic prediction models for emergency events relying on simulations of traffic incidents (e.g., lane closure). The outputs from the simulation model are used to adjust the predicted values of the regular model, thus making the model more adaptive to traffic incidents. However, to the best of our knowledge, none of the previous studies investigated the transferability of data-driven models for traffic prediction during emergency events. In this study, we develop a data-driven transfer learning method for traffic prediction during emergency events such as hurricane evacuation.

In addition, it is critical to predict traffic well ahead of time (e.g., greater than 1 hr.) during evacuation to provide transportation agencies enough time to deploy traffic management strategies (i.e., signal control, emergency shoulder use etc.). However, to accurately predict traffic for a longer time period, we need to account for demand variations over time. Most of the existing studies do not capture the demand variations while predicting future traffic. In our proposed method, to capture demand variations during evacuation, we incorporate both evacuation related features and regular traffic features to sequentially predict evacuation traffic flow for a long-term horizon (1 to 6 hours).

3. Problem Formulation

To implement the method, we construct a network of traffic detectors where each detector indicates a node. In this network, travel time between two nodes dynamically changes over time. To capture the dynamics, we define the network as a dynamic graph $\mathcal{G}_t(v, \mathcal{E}, \mathbf{A}_t)$ where v denotes the set of nodes (i.e., detectors) and $\mathcal{E}$ denotes the set of links between nodes (i, j) . $\mathbf{A}_t$ represents the connectivity between nodes as a weighted adjacency matrix, where weights are based on travel

time between any two nodes (i, j) , defined as follows:

$$\mathbf{A}_t(i, j) = \begin{cases} tt_{i,j}^t & \text{if } i \neq j \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

where $tt_{i,j}^t$ denotes the travel time between the nodes i and j at time t . The connectivity inside an adjacency matrix detects which neighboring nodes (j) will be influenced by the traffic condition at a given node (i). Moreover, in a time series problem the existing traffic condition at a given node (i) will also influence its future traffic condition, which means each node is temporally self-influenced. This is represented by adding an identity (I) matrix with the adjacency matrix which ensures that nodes are self-accessible,

$$\bar{\mathbf{A}}_t = \mathbf{A}_t + \mathbf{I} \quad (2)$$

We aim to *learn* traffic flow patterns in a transportation network over multiple time steps (i.e., future time series) based on capturing the influence of congestion propagation (i.e., travel time variations) on spatiotemporal cross correlation among nodes' traffic condition. In this problem, traffic condition is represented as a function of traffic demand related features. Thus, we feed the model with the information on two aspects: (i) a dynamic graph indicating the variations in travel time and (ii) node level features related to traffic demand. Let $\mathbf{X}_t$ be the input features and $\mathcal{G}_t(v, \mathcal{E}, \mathbf{A}_t)$ is a dynamic graph with weighted adjacency matrix $\mathbf{A}_t$. The problem is defined as to learn a function $\mathcal{F}(\cdot)$ that maps l instances of input sequence $([\mathbf{X}_{t-l}, \mathbf{X}_{t-l+1} \dots, \mathbf{X}_t])$ to predict p instances of flow $(F_{t+1}, F_{t+2} \dots \dots F_{t+p})$ for the entire network. Mathematically, the problem is defined as follows:

$$\mathcal{F}([\mathbf{X}_{t-l}, \mathbf{X}_{t-l+1} \dots, \mathbf{X}_t]; [\mathcal{G}_{t-l}(v, \mathcal{E}, \mathbf{A}_{t-l})]) = [F_{t+1}, F_{t+2} \dots F_{t+p}] \quad (3)$$

where $l(= 0, 1, 2, \dots, l)$ and $p(= 1, 2, 3, \dots, p)$ indicate the input and output sequence, respectively; $\mathbf{X}_t$ indicates traffic related features (i.e. volumes, time periods etc.); $\mathbf{A}_t$ indicates the weighted adjacency matrix at time t ; and the vector F_{t+p} indicates the link flows for each link of the network at time $(t + p)$. We have added the description of the notations associated with the model development in Table 1.

4. Methodology

4.1 Learning Traffic Flow Dynamics of the Transportation Network

Traffic flow dynamics in a transportation network can be represented as a flow propagation process—traffic traversing from the origin node to the destination node via neighboring nodes. That is why, traffic condition of a given node influences the traffic condition of the neighboring nodes, in other words there exists a spatial correlation among these nodes. However, at any time step whether the traffic at a given node will reach any neighboring node or not depends on the travel time between these nodes, which changes over time. So, to model the traffic flow dynamics we need to represent travel time variations of the network and utilize this information while capturing spatial correlation among the nodes.

Table 1

Description of the Notation Associated with the Model Development

<i>Notation</i>	<i>Description</i>
$\mathcal{G}$	<i>Transportation network</i>
v	<i>Set of nodes in $\mathcal{G}$ with size of $v = N$</i>

$\mathcal{E}$	<i>Set of links in $\mathcal{G}$ with size of $\mathcal{E} = E$</i>
t	<i>Time stamp representing different hours of a day</i>
$\mathbf{A}_t \in \mathbf{R}^{N \times N}$	<i>Weighted adjacency matrix of $\mathcal{G}$, defined by Equation (1)</i>
$\mathbf{I} \in \mathbf{R}^{N \times N}$	<i>Identity matrix</i>
$\bar{\mathbf{A}}_t \in \mathbf{R}^{N \times N}$	<i>Neighborhood matrix defined by Equation (2)</i>
$\bar{\mathbf{D}}_t \in \mathbf{R}^{N \times N}$	<i>Degree matrix of $\mathcal{G}$, a diagonal matrix where diagonal elements (i, i) indicate the number of links coming out from a node</i>
tt_{ij}	<i>travel time between nodes i and j</i>
l	<i>Input time sequence length (0,1, l)</i>
c	<i>Number of features at each node</i>
$\mathbf{X}_t^{reg} \in \mathbf{R}^{N \times c}$	<i>Contains all the traffic features (i.e., volumes, time periods etc.) associated with each node (i) of the network for regular condition</i>
$\mathbf{X}_t^{evc} \in \mathbf{R}^{N \times c}$	<i>Contains all the traffic features (i.e., volumes, time periods etc.) associated with each node (i) of the network for evacuation condition</i>
$\mathbf{X}_t^{eD} \in \mathbf{R}^{N \times c}$	<i>Contains the features related to evacuation travel demand (i.e., population under mandatory order, evacuation zones' location etc.) associated with each node (i) of the network</i>
$\mathbf{g}_t$	<i>Graph Convolutional filter to learn the congestion propagation inside the network</i>
$f(.)$	<i>Activation function</i>
$\mathbf{W}_{gc} \in \mathbf{R}^{N \times N}$	<i>Learnable parameters for the convolution filter</i>
h	<i>Indicates the output vector from different hidden layers of the proposed neural network architecture</i>
p	<i>Prediction horizon (1, p)</i>
$\mathbf{F}_{t+p} \in \mathbf{R}^E$	<i>Flow vector contains flows for each link (segment) of the network for the prediction horizon p</i>

All the bold letters denote a matrix

In this study, we develop a graph convolution based deep neural network architecture to capture spatiotemporal correlation among node-level traffic features for predicting traffic flows. The model has two layers (see Fig. 1): in the first layer, we apply a graph convolution operation to capture the spatial correlation among neighboring nodes. In this approach, we derive a graph convolutional filter from adjacency matrix which represents the travel time variations of the network, thereby detects which neighboring nodes are within the shortest path distance of the origin node at a given time step. To derive the convolutional filter, we adopt a graph theoretic approach where a graph adjacency matrix is decomposed into its eigenvalues to represent the structural properties of the graph such as the strength of a node (i.e., node level features) and shortest path between two nodes. Such a representation, when fed into a deep learning model, suffers from exploding or vanishing gradient problem due to sparsity in eigen values' distribution. To overcome this exploding or vanishing gradient problem, Kipf and Welling (Kipf and Welling, 2016) proposed a normalization technique to represent a graph and its intrinsic dynamics. We adopt a similar approach and define the graph as a symmetrically normalized adjacency matrix $(\bar{\mathbf{D}}_t^{-\frac{1}{2}} \bar{\mathbf{A}}_t \bar{\mathbf{D}}_t^{-\frac{1}{2}})$. However, in previous applications the networks were static, hence the normalized

adjacency matrices were fixed. In our case, the network is dynamic, hence the normalized adjacency matrix will change over time.

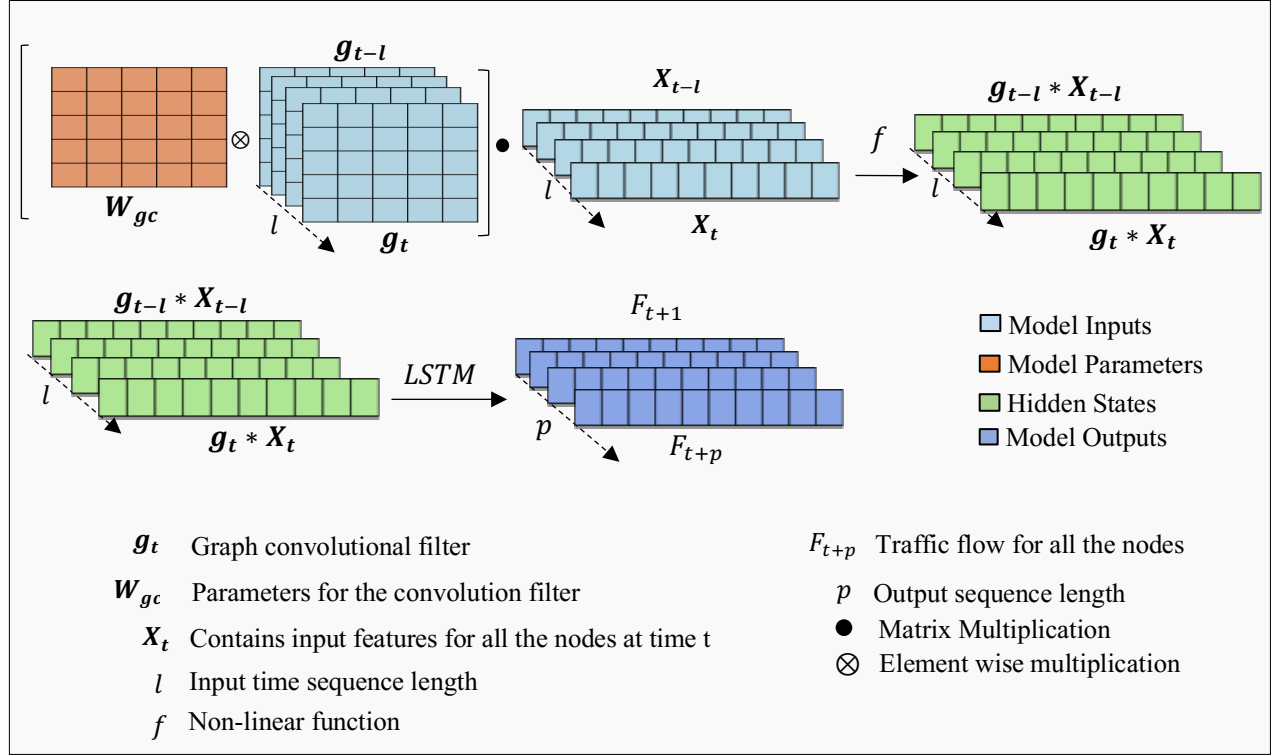


Fig. 1. A dynamic graph learning approach for network-wide traffic prediction

The main function of the graph convolution layer is to capture spatial cross correlation among nodes considering network wide travel time variations. We use the normalized graph adjacency matrix as a convolution filter and perform the convolution with node level traffic demand related features of the network. The convolution operation can be defined as follows:

$$gc_t = (W_{gc} \otimes (\bar{D}_t^{-\frac{1}{2}} \bar{A}_t \bar{D}_t^{-\frac{1}{2}})) X_t \quad (4)$$

where gc_t indicates the convoluted feature matrix and W_{gc} indicates the parameters for the convolution filter. The convoluted feature matrix represents the state transition of the network, in other words how congestion is propagating inside the network and influencing neighboring nodes.

In the second layer, we apply an LSTM (Hochreiter and Uergen Schmidhuber, 1997) model to map this convoluted feature matrix into traffic flows. The LSTM model captures the temporal dependency among traffic features while predicting traffic flows over multiple time steps (i.e., future time series). The proposed dynamic graph-based LSTM model (*DGCN-LSTM*) model can be defined as follows:

$$F_{t+p} = \text{LSTM}(f(gc_t)) = \text{LSTM}(f(W_{gc} \otimes (\bar{D}_t^{-\frac{1}{2}} \bar{A}_t \bar{D}_t^{-\frac{1}{2}})) X_t) \quad (5)$$

where f indicates a nonlinear activation function; we use rectified linear unit (relu) as an activation function.

Training such graph-based models over a transportation network requires a substantial amount of data. However, evacuations usually take place for 2 to 5 days before the hurricane landfall.

When a model is trained with a small sample it will cause the model to overfit. To overcome this problem, we develop a new modeling method adopting a transfer learning technique (Zhuang et al., 2021). We first train the *DGCN-LSTM* model over regular traffic data ($\mathbf{X}_t = \mathbf{X}_t^{reg}$) and later transfer this model to an evacuation period. The following section describes the methods to implement the model for evacuation traffic prediction.

4.2 Network-wide Evacuation Traffic Prediction

Evacuation traffic depends on many factors such as zonal level population under mandatory evacuation, hours left before landfall, distance of a detector from the nearest evacuation zone, and different time periods of the day etc. (Rahman et al., 2021c). Using these features as inputs, we can develop a simple time series-based model to predict evacuation traffic flow. However, such a model will perform poorly since it cannot capture the spatiotemporal dependency of traffic variables as it does not have any information on the underlying contexts of congestion propagation in the network. To overcome this problem, we adopt a transfer learning approach to transfer the context of network dynamics over multiple time steps (temporal sequences). However, traffic demands during evacuation significantly differ from non-evacuation condition. For example, evacuation traffic demand is higher than non-evacuation period and does not follow any regular pattern. Thus, when applying the transfer learning approach, we need to transfer only the information relevant for an evacuation period such as information of network connection and the function of how traffic flows from an upstream to a downstream location.

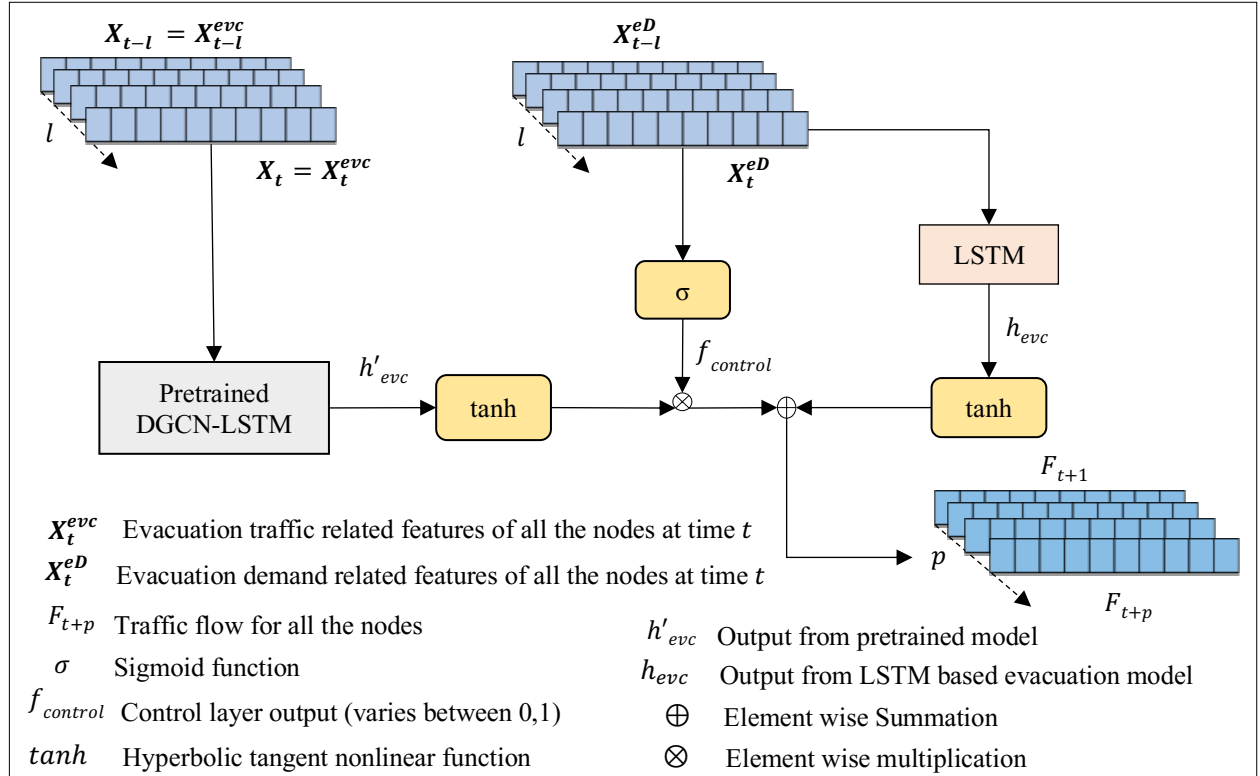


Fig. 2. A deep learning architecture for evacuation traffic prediction

We develop a deep learning architecture which controls the information flow from regular traffic condition to evacuation traffic condition. The proposed deep learning architecture has four components (see Fig. 2). The first component is the *pretrained DGCN-LSTM* model, we apply this

model using the traffic features (i.e., volumes, time periods etc.) from evacuation period ($\mathbf{X}_t = \mathbf{X}_t^{evc}$) to predict traffic flow over multiple timesteps.

$$h'_{evc} = DGCN-LSTM(\mathbf{X}_t^{evc}) \quad (6)$$

where h'_{evc} indicates the outputs from the *DGCN-LSTM* model. We add this information with other evacuation traffic demand information. The second component is an LSTM layer, we apply this model to capture the temporal correlation among evacuation traffic demand related features ($\mathbf{X}_t^{eD}$).

$$h_{evc} = LSTM(\mathbf{X}_t^{eD}) \quad (7)$$

where h_{evc} indicates the output from the LSTM layer.

The third component is the control layer; in this layer, we define a neural network with sigmoid activation function to remove irrelevant information from the *DGCN-LSTM* model.

$$f_{control} = \sigma(\mathbf{W}_c \cdot \mathbf{X}_t^{eD} + b_c) \quad (8)$$

where $f_{control}$ indicates the output from the control layers which are distributed between 0 to 1.

The fourth and final component is the output layer which adds the network dynamics related information with evacuation demand to generate the final traffic prediction.

$$F_{t+p} = f_{control} \otimes \tanh(h'_{evc}) + \tanh(h_{evc}) \quad (9)$$

In this layer, we perform an elementwise matrix multiplication between $f_{control}$ and h'_{evc} , thus some of the information will be erased prior to adding with evacuation demand. Since we assign weight $\mathbf{W}_c$ in the control layer, when training the model for evacuation traffic prediction, it automatically learns to control the information flow from non-evacuation condition to evacuation condition.

5. Data Collection and Preprocessing

5.1 Traffic Detector Data

To test the model, we consider a network consisting of interstate highways of Florida. We select the network based on evacuation traffic patterns in previous hurricanes, when many residents living in Florida evacuated to Georgia and adjacent States (Rahman et al., 2021c; Roy et al., 2021). Thus, two major highways (I-75 and I-95) and other two highways (I-4 and Florida's Turnpike) connecting them are expected to serve a substantial amount of evacuation traffic during Hurricane Irma. To create the network, we have chosen the northbound directions of I-75, I-95, and Florida's Turnpike and the eastbound direction of I-4 (see Fig. 3).

We have collected traffic data from Regional Integrated Transportation Information System (RITIS) ("REGIONAL INTEGRATED TRANSPORTATION INFORMATION SYSTEM: A data-driven platform for transportation analysis, monitoring, and data visualization," 2008) from September 4, 2017 to September 9, 2017 which covers the evacuation period of Hurricane Irma. We have also collected non-evacuation period traffic data from May 1 to August 31, 2017. RITIS gathers data from Microwave Vehicle Detection System (MVDS) detectors deployed by Florida DOT (<https://www.fdot.gov/>), giving real-time information on traffic speed, volume, and occupancy at a very high resolution (20 to 30s frequency).



Fig. 3. Network of inter-state highways

The raw data collected from traffic detectors are subjected to errors. Several factors such as detector malfunctioning, false encoding during storing the data into the server, overlapping of multiple entries, duplicate entries, and bad weather conditions can cause errors. Moreover, during congested stop and go traffic conditions, sometimes microwave radar detectors fail to detect vehicles, hence providing misleading information. Therefore, before proceeding to any data analysis, we need extensive data cleaning and quality checking. Fig. 4 shows the framework for the data processing steps.

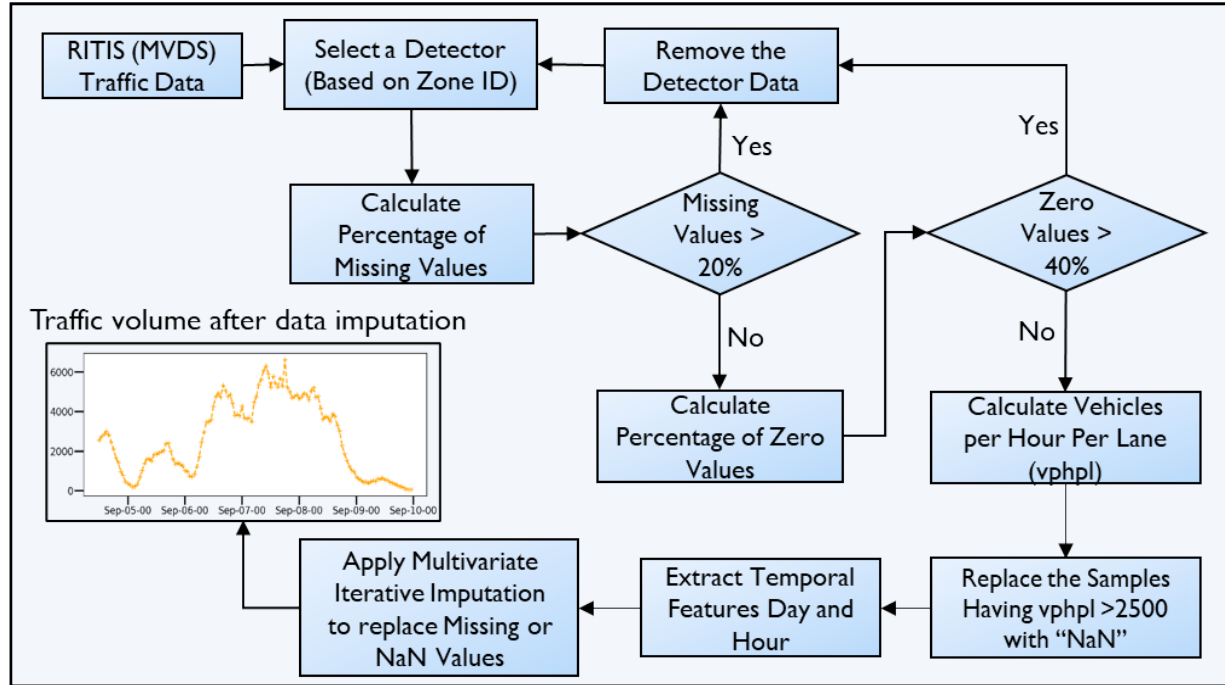


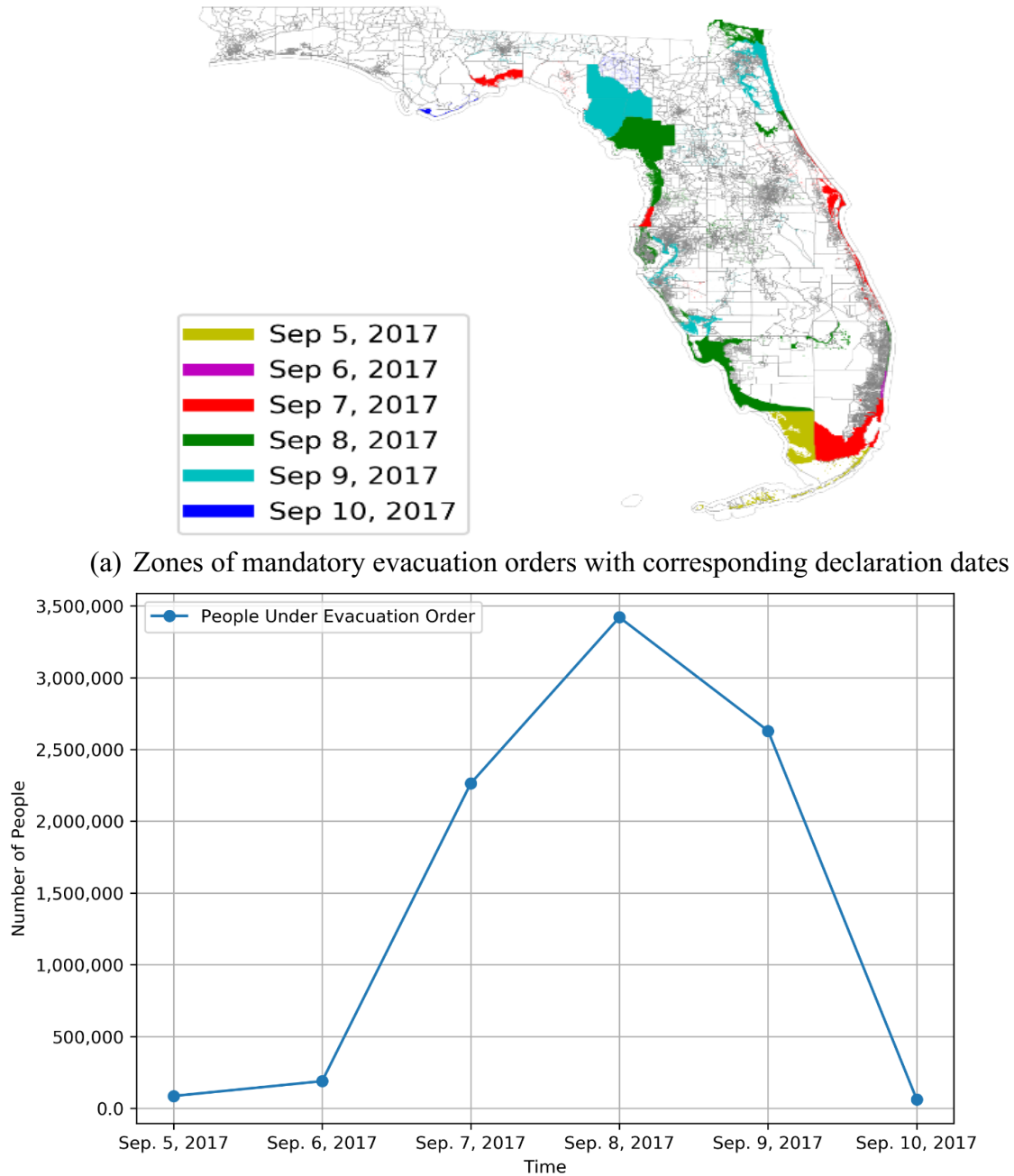
Fig. 4. Framework for data processing

We followed several steps for data processing. First, we remove the detectors having higher percentages of missing values ($>20\%$); second, we detect the outliers based on the capacity of the highway (2500 vehicle per hour per lane); third, we replace the outliers and available missing values using multivariate iterative data imputation technique (Pedregosa et al., 2011; van Buuren and Groothuis-Oudshoorn, 2011). The details of the data pre-processing steps are provided in our previous publication (Rahman et al., 2021c).

5.2 Zonal Level Mandatory Evacuation

We collect the time and location of evacuation orders issued for different areas for Hurricane Irma from the Florida Division of Emergency Management. However, the declaration dates of evacuation order for all the zones are not available at a single source, thereby, in few cases, we collect the declaration date by manually checking the emergency management agency's social media posts (e.g., Twitter, Facebook) of the respective county and contemporary news article available online. Fig. 5 (a) shows the mandatory evacuation zones with evacuation declaration times for our study area. We observe that most of the evacuation zones are by the coast; smaller zones in the central part of Florida mainly represent mobile homes or low-lying areas vulnerable to inland flooding. Florida Keys and other low-lying zones such as Everglades were issued mandatory order on early September 5, 2017. Evacuation zones in the east coast, such as Miami-Dade, Daytona were issued evacuation orders on September 7, 2017 (Hurricane Irma was supposed to hit the east coast of Florida until Sep. 7, 2017). After September 7, 2017, as the projected path shifted from east coast to west coast, evacuation zones of Naples, Cape Corals, Tampa, Levy, and Jacksonville were ordered mandatory evacuations on September 7 and onward (see Fig. 5 (a)). We have collected population data for the mandatory evacuation zones to understand how many people were under mandatory evacuation order. Since, population data is not available for the evacuation zones, we collect block group level population data from 2017 5-year American Community Survey and sum the population that falls within an evacuation zone to retrieve the population for

that zone. On Sept. 8, 2017, the highest number of people (3.42 million) were under mandatory evacuation orders, followed by Sept. 9, 2017 when the second-highest number of people (2.63 million) were under mandatory evacuation orders (Fig. 5(b)).



6. Experiments

6.1 Feature Extraction and Graph Representation

We followed several steps to extract the spatiotemporal features from the collected data. We prepared two types of data samples: (i) traffic data samples for regular period ($\mathbf{X}_t = \mathbf{X}_t^{reg}$) and evacuation period ($\mathbf{X}_t = \mathbf{X}_t^{evc}$); (ii) evacuation demand features ($\mathbf{X}_t^{eD}$). All the input features are listed in Table 2.

6.1.1 Traffic data samples

We aggregate the traffic data for 1-hour intervals estimating traffic flow and average traffic speed. To capture the periodic nature of traffic flow variations, we group the hours into 6 different time periods such as late night, early morning, morning, noon, evening, and night. We represent these features using one hot encoding, which means that each of the six time periods is represented by an indicator variable (0,1). We also extract different features to capture traffic flow variations over previous day (t_{d-1}) and previous time period (t_{prd-1}) corresponding to current day (t_d) and current time period (t_{prd}) at time (t). The extracted features include previous day and time periods' mean and standard deviation of traffic flow (see Table 2). Since we do not have any data to indicate the characteristics of different zones (e.g., built environment characteristics, zonal level population etc.); we use a variable named "Zone ID" to represent zonal characteristics specific to the location of each detector. This variable also represents the ordering of the output sequence (i.e., 1 to 806) for all the detectors.

We formulate the traffic data sample as [number of samples (n), input time sequence (l), number of nodes (N), input features (c)]. Since we have collected the data from 806 detectors, the number of nodes, $N = 806$. We select input data sequence of 6 hours to predict traffic for the next 6 hours, leading to input time sequence length, $l = 6$ and prediction horizon length, $p = 6$. In total we have twelve input features ($c = 12$): Zone ID, Late Night (12am-4am), Early Morning (4am-8am), Morning (8am -12 pm), Mid-day (12 pm-4pm), Evening (4pm-8pm), Night (8pm -12am), mean traffic flow (q_t), previous day mean traffic flow ($\bar{q}_{t_{d-1}}$), previous day standard deviation of traffic flow ($sq_{t_{d-1}}$), previous time period mean traffic flow ($\bar{q}_{t_{prd-1}}$), and previous time period standard deviation in traffic flow ($sq_{t_{prd-1}}$).

For the non-evacuation period, we have the data for 2148 hours and for the evacuation period we have data for 120 hours. For evacuation and non-evacuation periods the input data has the shape as [120, 6, 806, 12] and [2148, 6, 806, 12], respectively and the target data has the shape as [120, 6, 806] and [2148, 6, 806], respectively.

Table 2 Description of input features

Variables	Description
Z	Zone ID: represent zonal characteristics specific to the location of each detector (i.e. 1,2,...,N)
t_{prd}	Time periods: Late Night (12am-4am), Early Morning (4am-8am), Morning (8am -12 pm), Mid-day (12 pm-4pm), Evening (4pm-8pm), Night (8pm -12am)
t_d	Different days corresponding to time t
q_t	Traffic flow at time t

$\bar{q}_{t_{d-1}}$	<i>Previous day mean traffic flow</i>
$sq_{t_{d-1}}$	<i>Previous day standard deviation of traffic flow</i>
$\bar{q}_{t_{prd-1}}$	<i>Previous time period mean traffic flow</i>
$sq_{t_{prd-1}}$	<i>Previous time period standard deviation of traffic flow</i>
S_t	<i>Mean speed over an hour</i>
T_t	<i>Hours left before landfall</i>
$P_{t_{evc}}$	<i>Cumulative population under mandatory evacuation</i>
$d_{t_{evc}}$	<i>Distance to the nearest evacuation zone from each detector</i>

6.1.2 Evacuation demand data samples ($\mathbf{X}_t^{ep}$)

We extract features related to evacuation demand such as population in mandatory evacuation zone, distance of a detector from the nearest evacuation zone, and hours left before hurricane landfall. We have also added a variable “cumulative population under mandatory evacuation” to capture the impact of population under mandatory orders on overall traffic conditions. However, prior to adding this variable, we also need to consider that when an evacuation order is placed, it will take some time for people to start evacuating. That means that the number of populations under mandatory evacuation will not have an immediate effect on traffic condition. Rather we will observe the impact when people start to evacuate. For example, if 500,000 populations are under mandatory evacuation during early morning (e.g., 8 am) and people start evacuating from the evening (e.g., 8 pm), then we will observe an increase in overall traffic volume during the evening period. So, population under mandatory evacuation on morning (e.g., 8 am, $t - 12$) will have an impact on increase in traffic volume during evening (8 pm, t), which implies that there is a time lag between the declaration of evacuation orders and when people start to evacuate. To account this time lag, we shift the total population under mandatory evacuation zone by 18 hr. We perform an empirical analysis by running a linear regression model multiple times with different time lags and find that the coefficient associated with the variable of total population under mandatory orders is positive for 18-hour time lag ($t - 18$) and significantly influences the increase in evacuation traffic flow at time t . The details of this process of determining the time lag are provided in (Rahman et al., 2021c).

Moreover, evacuation demand also depends on time of the day. In our previous study (Rahman et al., 2021c), we found that people are more likely to evacuate during daytime compared to night time. Hence, we also consider time periods to capture evacuation traffic demand. Finally, the evacuation demand data samples have 9 features: Late Night (12am-4am), Early Morning (4am-8am), Morning (8am -12 pm), Mid-day (12 pm-4pm), Evening (4pm-8pm), Night (8pm -12am), population under mandatory evacuation zone (P_{evc}), distance of the nearest evacuation zone from each detector (d_{evc}), and hours left before hurricane landfall (T_t). We formulate the evacuation demand data as [number of samples (n), input time sequence (l), number of nodes (N), input features (c)] i.e. [120, 6, 806, 9].

6.1.3 Graph Representation

We follow several steps to construct the graph. First, we map locations of the detectors on Open Street Map. Second, considering the detectors as nodes, we connect these detectors to complete the network. Finally, after constructing the network, we represent the network using an adjacency matrix (see Equations 1 and 2). We also calculate the travel distance between pairs of nodes from Open Street Map and estimate the travel time. We define the travel time between a pair of nodes as follows,

$$tt_{ij}^t = \frac{d_{ij}}{\frac{s_i^t + s_j^t}{2}} = \frac{2d_{ij}}{s_i^t + s_j^t} \quad (10)$$

where tt_{ij}^t, d_{ij} indicate the travel time and distance between two consecutive detectors; S_i and S_j indicate average speed for two consecutive detectors. We use the travel time as weight for the adjacency matrix. We also perform gaussian transformation on the weighted graph adjacency matrix,

$$A_t(i, j) = \begin{cases} \exp\left(-\frac{(tt_{ij}^t)^2}{(tt_{std}^t)^2}\right), & \text{if } i \neq j \text{ and } \exp\left(-\frac{(tt_{ij}^t)^2}{(tt_{std}^t)^2}\right) \geq r \\ 0, & \text{otherwise} \end{cases} \quad (11)$$

where tt_{std} indicates the standard deviation of travel time and r is the threshold to control the distribution and sparsity of weighted graph adjacency matrix. We fix the threshold value as 0.1 based on previous studies (Li et al., 2018b) and experiment results.

6.2 Baseline Models

We implement three baseline models to compare the performance of the proposed DGCN-LSTM model.

6.2.1 LSTM

In the *LSTM* model, we use two stacked *LSTM* layers to predict traffic for next 6 hours. For each layer, we assign 4836 (number of nodes * output sequence length) hidden neurons. The output layer is a fully connected layer with tanh activation function.

6.2.2 Convolutional LSTM

In the Convolutional LSTM (*ConvLSTM*) model, we stack a convolution layer with an *LSTM* layer. The convolutional layer uses a convolution filter to extract the spatial correlation among traffic features between consecutive detectors. We experiment with different size of the kernel (k) and find that the model performs best for a kernel size of 3. The output from the convolutional layer is fed into the *LSTM* layer to capture temporal correlation among traffic features while predicting traffic flow over a long sequence.

6.2.3 Graph Convolutional LSTM

In the graph convolutional LSTM (*GCN-LSTM*) model, we apply a similar approach as (Kipf and Welling, 2016; Li et al., 2018b). In this case, the weights of the graph adjacency matrix are constant and assigned based on the distance between two consecutive nodes.

6.3 Model Training

We train the model using mean squared error as the loss function. At each iteration, the model estimates the mean squared error for the predicted flows ($\hat{F}_{t+p}^\varepsilon$) and the actual flows (F_{t+p}^ε) of the network. Afterward, the gradient of the loss function is backpropagated to adjust the weights to reduce loss function value. The loss function can be defined as,

$$L = Loss(F_{t+p}^\varepsilon, \hat{F}_{t+p}^\varepsilon) \quad (12)$$

where $Loss(.)$ is the function to estimate the error between the actual (F_{t+p}^ε) and estimated values ($\hat{F}_{t+p}^\varepsilon$) and ε denotes the set of links for the network.

We implement our model using Pytorch environment (“PyTorch,” 2016) and train the model with dual NVIDIA Tesla V100 16GB PCIe GPU.

6.3.1 DGCN-LSTM for Non-evacuation period

From the regular traffic data samples, we use 90% for training, 5% for validation, and rest 5% of the data for testing the model. Based on the validation accuracy, we tune the hyperparameters such as learning rate, maximum number of iterations, and the type of the optimizer. We also track the training and validation loss values to check whether the model is overfitting or not. From the loss values, we find that it takes about 60 epochs with a learning rate of 0.001 for the model to converge (i.e., similar train and validation loss value). After that there are merely any variation in loss values (Fig. 6 (a)). Moreover, after 70 epochs the value of the loss function for the validation data gradually starts increasing, indicating that the model starts to overfit. We use Adaptive Moment Estimation (ADAM) to train the model. Compared to other optimizers such as Adaptive Gradient (AdaGrad), Root Mean Square Propagation (RMSProp) etc., ADAM optimizer gives more stable solutions.

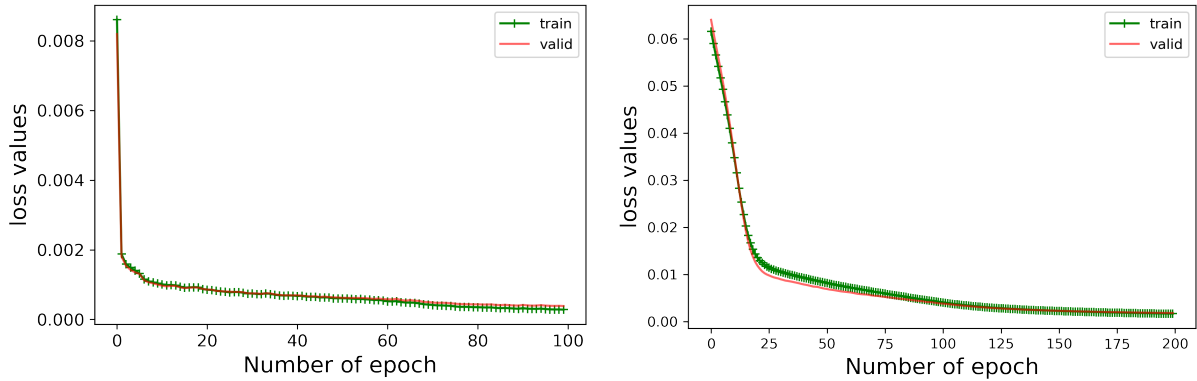


Fig. 6. Variations of training and validation loss (a) DGCN-LSTM (b) Transfer Learned DGCN-LSTM

6.3.2 Transfer Learned DGCN-LSTM for Evacuation period

From the evacuation traffic data samples, we use 80% for training, 10% for validation, and rest 10% of the data for testing the model. Similar to previous model, we experimented with different optimizer however ADAM optimizer gives the best result. We also track the changes in training and validation loss values to ensure the model is not overfitting. It takes 150 epochs for the model to converge, after that it starts to overfit (Fig. 6(b)).

6.4 Experiment results

Once the final model is fixed, we test it on the test data set. We calculate Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and Symmetric Mean Absolute Percentage Error (SMAPE) as performance measures to check the accuracy of the implemented model. Performance metrics are defined as:

$$RMSE = \sqrt{\frac{1}{p} \sum_{p=1}^p \frac{1}{E} \sum_{\mathcal{E}=1}^E (F_{t+p}^{\mathcal{E}} - \hat{F}_{t+p}^{\mathcal{E}})^2} \quad (13)$$

$$MAE = \frac{1}{p} \sum_{p=1}^p \frac{1}{E} \sum_{\mathcal{E}=1}^E |F_{t+p}^{\mathcal{E}} - \hat{F}_{t+p}^{\mathcal{E}}| \quad (14)$$

$$SMAPE = \frac{100}{p} \sum_{p=1}^p \frac{1}{E} \sum_{\mathcal{E}=1}^E \frac{|F_{t+p}^{\mathcal{E}} - \hat{F}_{t+p}^{\mathcal{E}}|}{(|F_{t+p}^{\mathcal{E}}| + |\hat{F}_{t+p}^{\mathcal{E}}|)} \quad (15)$$

where $\mathcal{E}$ indicates the set of available links and E indicates the total number of links in the network. In case of our network, we have $E = 865$ links.

In Table 3, we report the performance of the model on the test dataset. To investigate the sensitivity of the model over different data samples, we iteratively train the model 10 times with different training data and measure the accuracy on test data. At each iteration, we randomly split the data into train, validation, and test sets. Since we randomly split the data at each iteration, we have different data for training, validation and testing the model. These datasets are temporally ordered to maintain the temporal sequence of time series input. From this process, we obtain 10 different models and report the mean and standard deviation of the estimated performance measures on the test datasets. Based on performance measures, we find that the proposed *DGCN-LSTM* model performs best compared to other baseline models. The RMSE and MAE values of the model are 226.85 and 133.82, respectively.

However, when we apply the model for traffic prediction during evacuation, it performs poorly. The RMSE and MAE values significantly increase to 1440.994 and 1009.94, respectively (Fig. 7). To resolve this issue, we first train the model over the data that combine both regular and evacuation period observations. In the combined dataset, we also include the evacuation specific variables; for regular period data, the evacuation specific variables are padded with zeros. We test the combined *DGCN-LSTM* model for evacuation period traffic prediction and find a slight improvement in model performance with RMSE and MAE values reduced to 1097.23 and 733.99, respectively (Table 4). However, the overall performance is still poor compared to that in a regular period.

Hence, we use a transfer learning approach with additional demand features to capture the changes in traffic demand during hurricane period, which improves the overall prediction accuracy. For the transfer learned model, the RMSE and MAE values are 399.69 and 268.03, respectively (Table 4).

The RMSE and MAE values provide aggregate information (average over all the outputs) on the performance of the models. In Fig. 8 (a), we show the correlation between actual and predicted

link flows. From the figure we find that the actual and predicted traffic flows almost match with each other with an R^2 score of 0.98 indicating that the model can learn regular traffic flow patterns very well. Although R^2 is an aggregate measure of model performance, R^2 is easier to interpret since it is normalized between -1 and 1.

We also find that in some cases the model overestimates and underestimates the flows. This is because of the shift in hurricane path three days before the landfall day and associated changes in mandatory evacuation zones from southeast regions (e.g., Miami) to southwest regions (e.g., Tampa) of Florida. This sudden change caused an increase in evacuation traffic at the upstream of I-75 and a decrease in evacuation traffic at the upstream of I-95. Due to such sudden variations, the model fails to accurately capture the trends, resulting in overestimation and underestimation of traffic flows.

We also investigate the detector wise variations of actual and predicted traffic flows (Fig.8 (b)). The overall symmetric mean absolute percentage error (SMAPE) for different prediction horizon remains less than 8%, which indicates that the model can capture spatiotemporal patterns of traffic very well.

Table 3

Comparisons among different models to predict traffic over 6-hour sequence for non-evacuation period

Model	Mean RMSE	Std RMSE	Mean MAE	Std MAE	Mean R^2 Score	Std R^2 Score
LSTM	282.38	14.24	160.81	3.92	0.98	0.0028
GCN-LSTM	275.08	14.08	152.08	5.91	0.98	0.0024
ConvLSTM	246.57	31.19	146.11	14.94	0.98	0.0046
DGCN-LSTM	226.84	21.54	133.82	9.58	0.98	0.0032

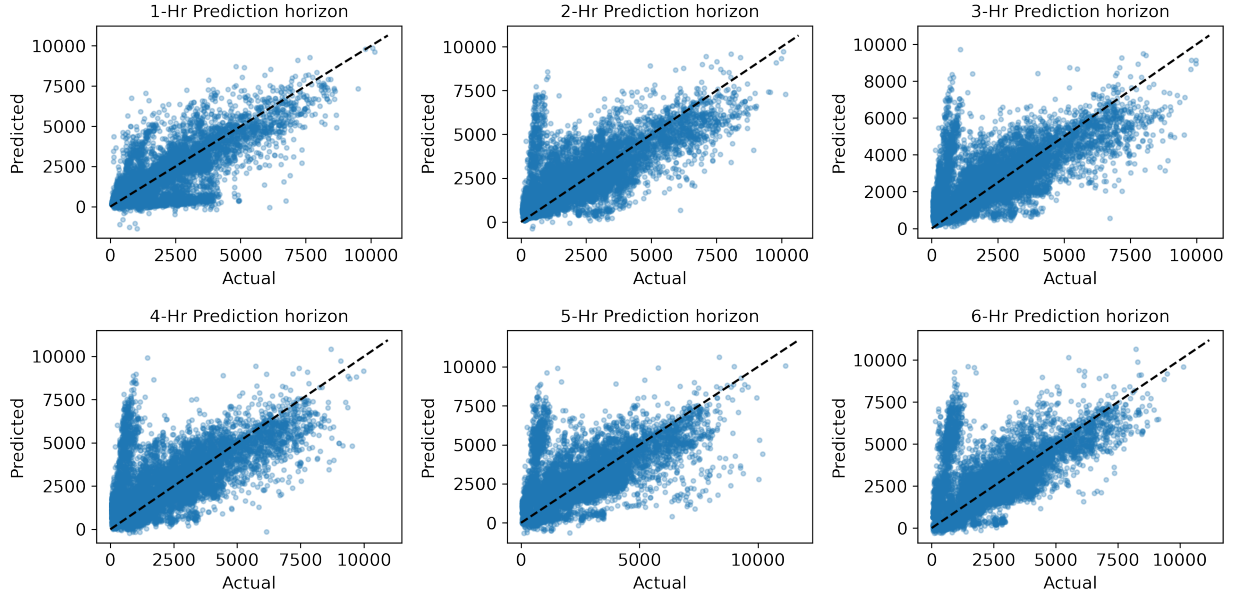
std = standard deviation

Table 4

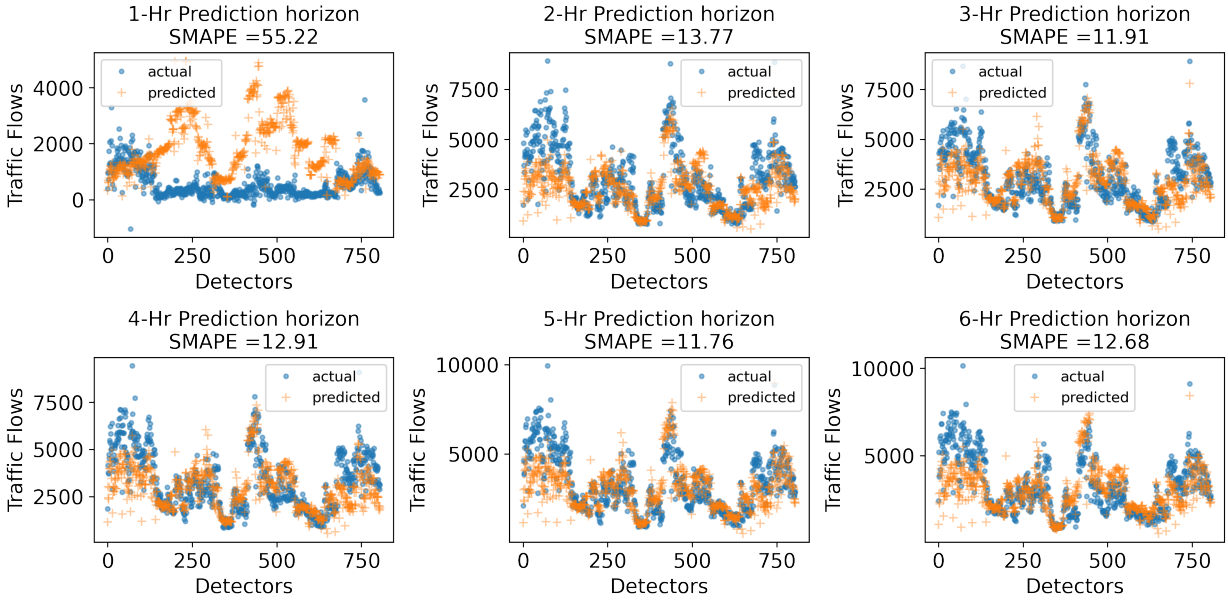
Proposed model performance for evacuation traffic prediction (Min flow 50.0 and Max flow 11247.0)

Model	RMSE	MAE	R^2 Score
LSTM	1481.17	1082.47	0.16
GCN-LSTM	1481.14	1014.08	0.20
ConvLSTM	1480.57	1076.85	0.20
DGCN-LSTM	1440.99	1009.94	0.21

Combined DGCN-LSTM	1097.23	733.99	0.33
Transfer learned DGCN-LSTM	399.69	268.03	0.94



(a)



(b)

Fig. 7. Comparison between actual and predicted traffic flow (a) correlation (b) variations over different detectors without transfer learning

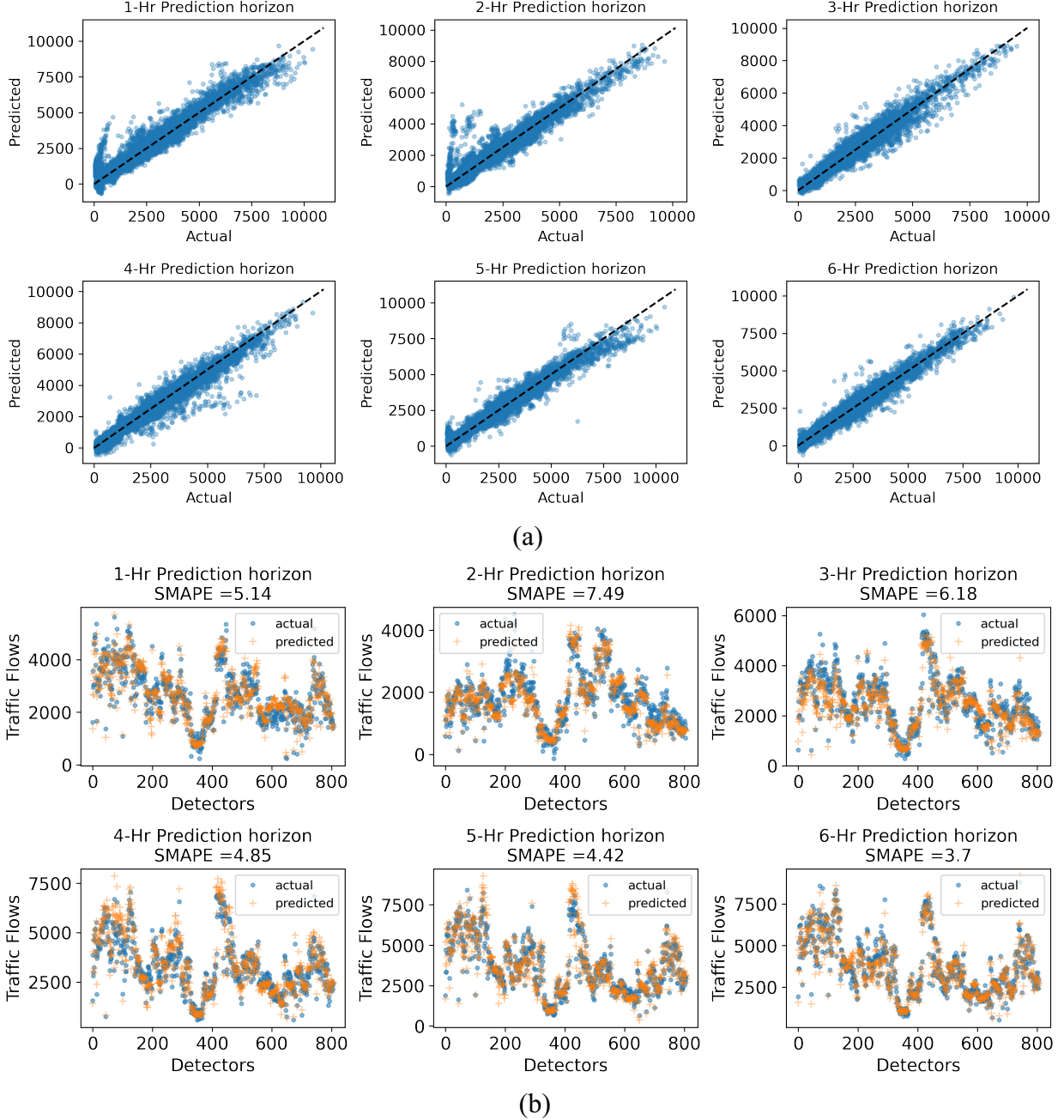
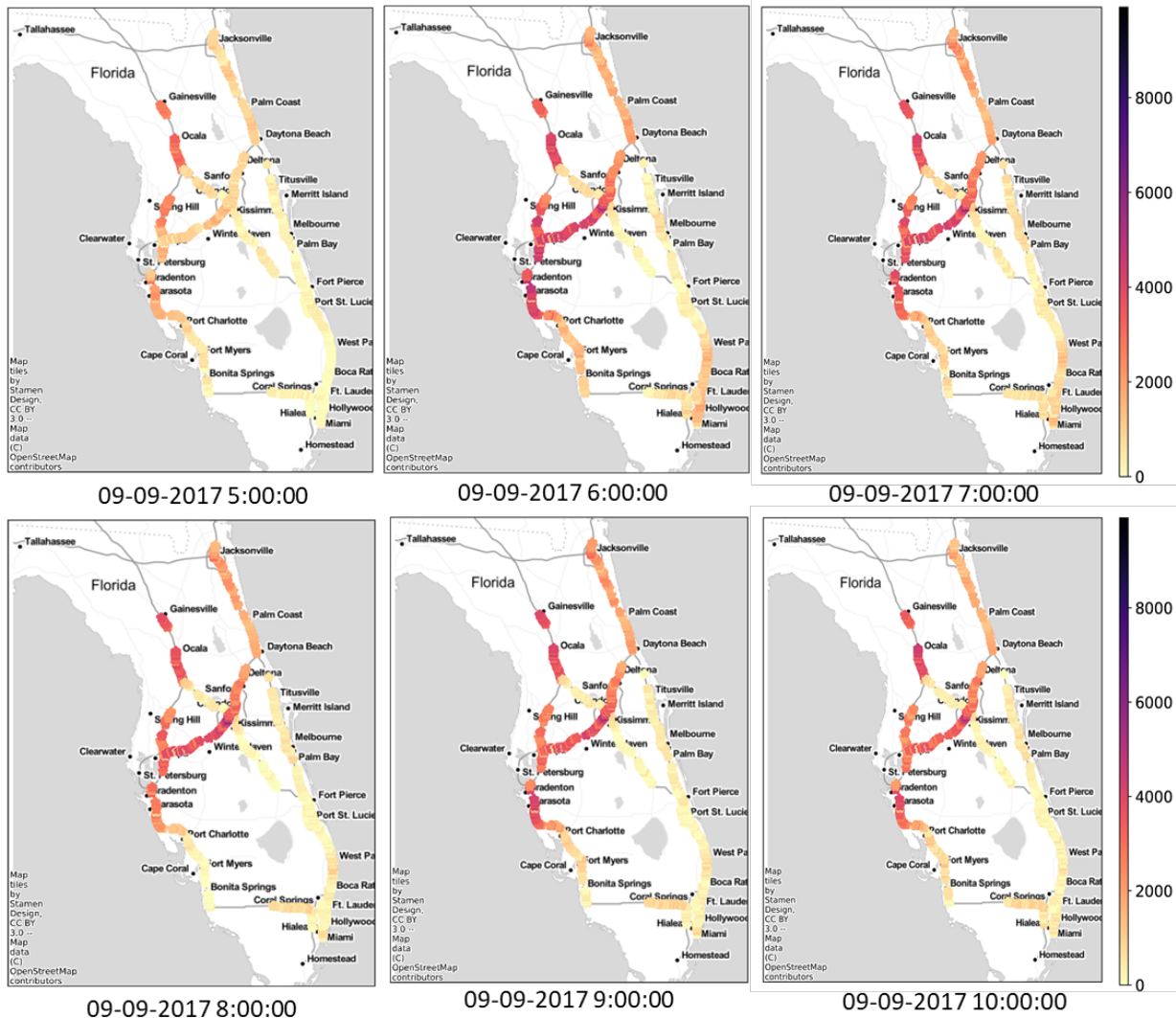


Fig. 8. Comparison between actual and predicted traffic flow (a) correlation (b) variations over different detectors with transfer learning

6.5 Congestion Mapping to Understand Network Disruption

We apply the implemented model to predict traffic for different days prior to hurricane landfall. As shown in Fig. 9, we map the predicted traffic flows to generate spatiotemporal traffic variations for different zones over a 6-hour period. The figure demonstrates congestion propagation at different zones of the network, such information will be critical for the traffic management agencies to implement strategies focusing on reducing delays during hurricane evacuation. The figure provides further evidence that the implemented model can capture the spatiotemporal traffic variations of a network during emergency evacuation even in case of unexpected event such as

changes in hurricane path changing zonal level evacuation demand. For example, we observe a significant traffic congestion near west coast of Florida region: downstream of I-75 and I-4 on September 8 and 9, 2017. This is because of the shift in hurricane Irma's projection path which forced people living in Naples, Cape Corals, Tampa, Levy, Jacksonville to evacuate at the eleventh hour causing significant congestion.



(a) Predicted traffic flow

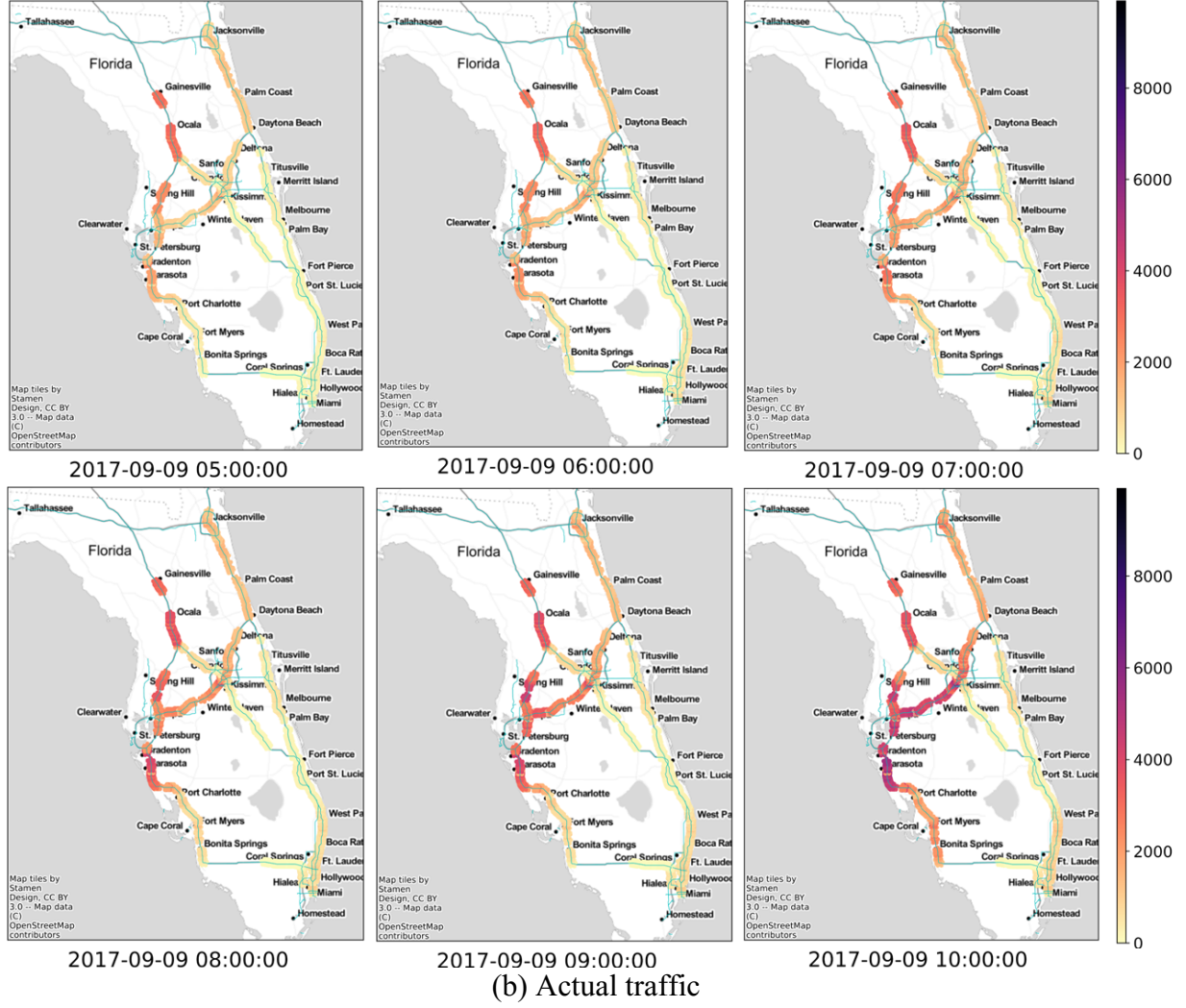


Fig. 9. Congestion map indicating traffic flow variations over different time during hurricane evacuation

7. Conclusions

Evacuation traffic prediction is one of the most critical elements for deploying pro-active traffic management strategies. However, evacuation traffic patterns differ from non-evacuation traffic condition such as the presence of higher traffic volume and unexpected shifts in evacuation trends. Thus, it is more challenging to learn such irregularities using traditional modeling approaches. Moreover, modeling spatiotemporal traffic variations requires large volume of data at a higher resolution, which is difficult to obtain due to the short duration of typical evacuation periods. To address these challenges, in this study we develop a new method considering spatiotemporal network dynamics to accurately predict evacuation traffic over multiple time steps.

First, we develop a deep learning architecture namely *DGCN-LSTM* to learn the spatiotemporal network scale traffic patterns and train the model with non-evacuation period traffic data. Based on the experiment results, we find that the implemented *DGCN-LSTM* outperforms the existing deep learning models (such as *LSTM*, *ConvLSTM* and *GCN-LSTM* models) with an RMSE of 226.84. However, as we apply the model for predicting traffic during evacuation periods the RMSE

value increased to 1440.99. We overcome this issue by adopting a transfer learning approach with additional evacuation demand related features such as distance from the evacuation zone, time to landfall, and other zonal level features to control the information flow from the pretrained *DGCN-LSTM* model. The final transfer learned *DGCN-LSTM* model performs well to predict evacuation traffic flow (RMSE 399.69).

The main contribution of this study includes the development of a big data pipeline to collect and analyze large-scale traffic detector data during emergency evacuation, thus providing insights on network-wide spatiotemporal patterns of evacuation traffic. Based on that it develops a data-driven method to accurately predict long-term traffic variations for a large-scale network. Such data-driven methods will assist emergency traffic management agencies to implement strategies focusing on reducing traffic delays during hurricane evacuation.

This study has several limitations. We have not tested the performance of the model over data from other hurricanes. Testing the model for multiple hurricanes will further establish the generalizability of the model for evacuation traffic prediction. Moreover, we do not have data related to zonal level evacuation traffic demand. We use aggregate measures such as total population under mandatory evacuation to understand overall evacuation trends. High resolution demand data from emerging technologies such as mobile phones, location-based services, and connected vehicles can be used to overcome this issue.

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